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TESIS DOCTORAL

Risk Premiumin the Global CreditMarkets: 2006-2012

La Prima de Riesgo en los Mercados Globales de Crédito: 2006-2012

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Álvaro Mª Chamizo Cana

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DOCTORAL DISSERTATION

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A mis padres, hermanos, familia y amigos

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Resumen

¿Qué hemos aprendido de la crisis ocurrida durante el periodo 2006-2012, que incluye eventos como la crisis “subprime” la bancarrota de Lehman Brothers, o la crisis de deuda soberana europea?

Normalmente, se asume que en las empresas que tienen CDS, éste es el factor clave para determinar la prima de riesgo de un nuevo activo. Por tanto, el CDS es un elemento fundamental para un inversor para tomar oportunidades relativas a través de la estructura de capital de la empresa. En el primer capítulo estudiamos los aspectos más relevantes de la microestructura del mercado de los CDS, en términos de precios, para tener una idea precisa del funcionamiento de este mercado. Consideramos que este tipo de análisis es fundamental para establecer una base sólida para el resto de los estudios empíricos que realizamos en los siguientes capítulos.

En su documento “Basel III: A global regulatory framework for more resilient banks and banking systems”, Basilea establece los requerimientos de capital por el riesgo de CVA en la cartera de negociación y la metodología para la determinación de dicho capital. Este requerimiento regulatorio añade una presión extra para el profundo conocimiento del mercado de los CDS y motiva el análisis llevado a cabo en esta tesis. El problema surge cuando tenemos que estimar la prima de riesgo de crédito de contrapartidas que no tienen CDS en el mercado. ¿Cómo podemos estimar el spread de crédito de un emisor sin CDS? Adicionalmente, a raíz del default de Lehman Brothers el 15 de septiembre de 2008, observamos la presencia de grandes “outliers” en la distribución de spread de crédito en las distintas combinaciones de rating, industria y región. Después de un exhaustivo análisis de los modelos estudiados, llegamos a las siguientes conclusiones. Es claro que la regresión jerárquica se ajusta mucho mejor que los modelos no jerárquicos. Adicionalmente, preferimos en general la estimación de los modelos en mediana que en media para asignar un spread a un emisor sin CDS, debido a la robustez de la mediana, que minimiza el problema de inversión. Por último, preferimos la mediana dada la presencia de asimetría a la derecha que suele mostrar la distribución de los spread de crédito.

En el tercer capítulo establecemos una metodología para el análisis de riesgo de crédito que puede ser integrado dentro del marco del apetito por riesgo de las entidades financieras. Comenzamos estableciendo un factor global de riesgo usando los datos de los CDS, y analizamos la información contenida en un amplio conjunto de variables financieras para el factor global de riesgo así como para el riesgo de crédito de los sectores. El factor global de riesgo que hemos estimado es utilizado para evaluar el riesgo sistémico e idiosincrático de los índices de crédito sectoriales. Nuestros resultados muestran que el sector más sistémico fue el sector fin-

anciero. De acuerdo con nuestra metodología, el sector industrial fue el segundo sector más sistémico durante este periodo de tiempo. Por otro lado, siguiendo con la misma línea de razonamiento, los dos sectores menos correlacionados con el resto de sectores han sido el sector de la salud y el tecnológico. Adicionalmente, se presenta una descomposición similar para los CDS de los emisores de los sectores financieros e industrial en Norte América y Europa. Dicha descomposición puede ser una importante herramienta para evaluar las posibilidades de diversificación de las carteras de crédito, así como para diseñar las estrategias de cobertura de las mismas. Este tipo de descomposición puede ser usado por las entidades financieras para fijar sus límites de riesgo cuando establecen su política de asignación de activos ("asset allocation") así como por los supervisores ocupados en la búsqueda de potenciales problemas de riesgo sistémico.

En el siguiente capítulo estudiamos la preocupación incesante de que la cobertura del ajuste de valoración crediticia (CVA) llegue a ser extremadamente difícil porque la correlación de largo plazo existente entre los CDS individuales y los índices de crédito deje de existir. Por lo tanto, en el capítulo 4 hemos analizado el riesgo empírico en una cartera de CDS, definiendo el riesgo de base que se induce de la correlación imperfecta entre el CDS individual y el índice de crédito (por ejemplo, Itraxx) involucrado en una estrategia de cobertura dinámica. Las instituciones financieras normalmente prefieren cubrir sus carteras de CDS o CVA con índices a causa de la alta liquidez de dichos índices. Si los cambios en los precios de los CDS y los índices estuvieran perfectamente correlacionados, no introduciríamos riesgos adicionales, y podríamos perfectamente compensar cualquier pérdida o ganancia tomando dinámicamente la posición contraria en el índice correspondiente. Pero hemos mostrado que dicho riesgo de base existe, incluso para carteras altamente diversificadas, con más de setecientos emisores, lo que significa que no podemos inmunizar completamente el valor de la cartera basándonos en índices para su cobertura, y asumiendo implícitamente que el riesgo idiosincrático se compensa entre los distintos emisores de una cartera.

Finalmente, en el último capítulo nos centramos en la correlación entre activos. La correlación entre los activos de las empresas es uno de los factores más determinantes cuando calculamos el capital que necesitamos para hacer frente a las pérdidas inesperadas de una cartera bajo el enfoque de modelos internos avanzados de Basilea, Basilea II, así que bajo muchos de los modelos de crédito de la industria financiera. Desafortunadamente, la correlación de activos no es directamente observable en el mercado, por lo que nos vemos forzados a usar diferente métodos para estimar dicha correlación de activos. En este capítulo argumentamos que la principal razón para el incremento del valor de riesgo crediticio durante este periodo fue el aumento de las correlaciones intrasectoriales e intersectoriales en los mercados de crédito, aunque también tuvo su relevancia el incremento de la probabilidad de default asignada por las agencias de ratings. Adicionalmente, mostramos que había señales en el mercado de crédito que el sector financiero probablemente no introdujo en sus modelos internos de crédito para gestionar sus riesgos durante la crisis.

Abstract

¿What have we learnt from the 2006-2012 crisis, including events such as the subprime crisis, the bankruptcy of Lehman Brothers or the European sovereign debt crisis, among others?

It is usually assumed that in firms that have a CDS quotation, this CDS is the key factor in establishing the credit premium risk for a new financial asset. Thus, the CDS is a key element for any investor in taking relative value opportunities across a firm's capital structure. In the first chapter we study the most relevant aspects of the microstructure of the CDS market in terms of pricing, to have a clear idea of how this market works. We consider that such an analysis is a necessary point for establishing a solid base for the rest of the chapters in order to carry out the different empirical studies we perform.

In its document "Basel III: A global regulatory framework for more resilient banks and banking systems", Basel sets the requirement of a capital charge for credit valuation adjustment (CVA) risk in the trading book and its methodology for the computation for the capital requirement. This regulatory requirement has added extra pressure for in-depth knowledge of the CDS market and this motivates the analysis performed in this thesis. The problem arises in estimating of the credit risk premium for those counterparties without a directly quoted CDS in the market. How can we estimate the credit spread for an issuer without CDS? In addition to this, given the high volatility period in the credit market in the last few years and, in particular, after the default of Lehman Brothers on 15 September 2008, we observe the presence of big outliers in the distribution of credit spread in the different combinations of rating, industry and region. After an exhaustive analysis of the results from the different models studied, we have reached the following conclusions. It is clear that hierarchical regression models fit the data much better than those of non-hierarchical regression. Furthermore, we generally prefer the median model (50%-quantile regression) to the mean model (standard OLS regression) due to its robustness when assigning the price to a new credit asset without spread, minimizing the "inversion problem". Finally, an additional fundamental reason to prefer the median model is the typical "right skewness" distribution of CDS spreads.

In the third chapter we provide a methodology for credit risk analysis that can be embedded into a risk appetite framework. We start by estimating a global risk factor using CDS data, and we analyse the information content in a wide set of financial indicators of the global risk factor as well as of credit risk at the sector level. The global risk factor is then used to evaluate the systemic and idiosyncratic components of credit risk for

sectorial credit indices. Our results show that the most systemic sector was the financial sector. According to our methodology, the industrial sector was the second most systemic during this period of time. On the other hand, along the same line of reasoning, the two sectors that are the least correlated with the rest have been the health care and technology sectors. In addition to this, a similar decomposition of credit risk is obtained for CDS issuers in the industrial and financial sectors of Europe and North America. Such decomposition can be an important tool when evaluating the diversification possibilities of credit portfolios as well as for the design of appropriate hedging strategies. It could be used by financial institutions to maintain their risk limits when taking their asset allocation decisions as well as by supervisors searching for potential systemic risk problems

In the following chapter we study the rising fears that CVA hedging will become increasingly difficult as the long-standing correlation between single-name and index CDS products breaks down. Therefore, in the fourth chapter, we have analysed the empirical risk in a CDS portfolio, defining basis risk as that induced by the imperfect correlation between the underlying single CDS contract to be replicated and the credit index contract involved in the dynamic replication strategy (e.g., iTraxx Index). Financial institutions usually prefer to hedge their CDS or CVA by trading in a credit index because of their higher liquidity and lower frictions. If changes in the price of the CDS and the price of credit index contracts were perfectly correlated, no further risk would be introduced, and one could perfectly offset any gain or loss in the position by dynamically trading in the related index contract. But we have shown that basis risk exists even in the case of a large diversified portfolio with more than seven hundred issuers, meaning that we cannot fully immunize the value of such a portfolio with a hedge based on credit index contracts and implicitly assuming that the idiosyncratic risk is offset among the different issuers in the portfolio.

Finally, in the last chapter, we focus on asset correlation. The correlation among a firm's assets is one of the most important factors when calculating the capital needed to face unexpected losses of a credit portfolio under the Internal Ratings-Based approach (IRB) of Basel, Basel II, and for many of the credit models in the financial industry. Unfortunately, the asset correlation is not directly observable in the market, thus we are forced to use different methods in order to estimate asset correlation. In this chapter, we have argued that the main reason for the increase in Credit VaR over time has been the growing intra-sector and inter-sector correlations among credit markets. Also worth noting is the increase in the average probability of default of the issuers provided by the external rating. In addition to this, we show that there were signs in the credit market that the financial sector probably did not introduce them into their internal risk models in order to manage their risk during the crisis.

Global summary

Global introduction

¿What have we learnt from the crisis occurred during 2006-2012, including events such as the subprime crisis, the bankruptcy of Lehman Brothers or the European sovereign debt crisis, among others?

In its document "Basel III: A global regulatory framework for more resilient banks and banking systems", the Basel Committee (2011) sets the requirement of a capital charge for CVA risk in the trading book and its methodology for the computation for the capital requirement. In a later document, "Basel III counterparty credit risk and exposures to central counterparties - Frequently asked questions", the Basel Committee (2012b) reaffirms the idea of requiring the financial entities to estimate credit spread curves, considering the different factors of rating, sector and region of each counterparty. Credit valuation adjustment (CVA) is defined as the difference between the risk-free portfolio value and the true portfolio value that takes into account the possibility of a counterparty's default. In other words, CVA is the market value of counterparty credit risk. Those entities coping with advanced models in their risk management are facing the problem of the determining of the credit spread for the counterparties in their portfolios and, even more, the hedging strategies to follow using either single-name CDS or index CDS. This regulatory requirement has added extra pressure for in-depth knowledge of the CDS market and this motivates the analysis performed in this thesis.

In Chapter 1, we study the most relevant aspects of the microstructure of the CDS market in terms of pricing, to have a clear idea of how this market works. We consider that such analysis is a necessary point for establishing a solid base for the rest of the chapters in order to carry out the different empirical studies we perform, designed to answer, among others, the following questions:

What type of restructuring clause should we use to aggregate the different CDS data? Which currency should we use to estimate our credit curves? How can we manage the different standard recovery rates in the market? What type of filter should we apply to the dataset?

Any type of investment requires the acquisition of assets (financial, real or both), and hence analysing their different features is crucial. The three main attributes of financial assets are return, risk, and liquidity. The first two are generally taken into consideration when deciding whether to invest in an asset or not. However, the financial crisis has made of liquidity a central risk factor. Therefore, investors must analyse risk, return and liquidity characteristics of those financial assets before taking their investment decision [Altman (1996), Cebenoyan and Strahan (2001), James (1996) and Guill (2008)]. In relation to this idea, in Chapter 2 we pay attention to the determination of credit spreads with different econometric models. This is decisive for any financial entity for several reasons:

- The assignment of prices for new loans, or financial guarantees, especially because of its implications for the valuation of the banking book.
- Using market-implied ratings instead of agency ratings for the monitoring of the loan portfolio.
- CVA quantification of the trading book for those counterparties with no direct liquid CDS quoted in the market.

It is usually assumed that in firms that have a CDS quotation, this CDS is the key factor in establishing the credit premium risk for a new financial asset [see Longstaff et al. (2003) and Longstaff et al. (2005)]. Thus, the CDS is a key element for any investor in taking relative value opportunities across a firm's capital structure. All this being true, the problem arises in estimation of the credit risk premium for those counterparties without a directly quoted CDS in the market. And in this case, two main questions must be answered:

How can we estimate the credit spread for an issuer without CDS? In addition to this, given the high volatility period in the credit market in the last few years and, in particular, after the default of Lehman Brothers on 15 September 2008, we observe the presence of big outliers in the distribution of credit spread in the different combinations of rating, industry and region. In the context of the current financial and economic crisis, it is natural to ask whether the ordinary least-squares (OLS) regression is the optimal method to estimate credit spread curves. Or could it be more efficient to use more robust estimators that are not so affected by the presence of outliers? For a financial institution, it is clear that the best approach is the one that best reflects market trends, while minimizing the fluctuations in the implied estimates.

In Chapter 3, we provide a methodology for credit risk analysis that can be embedded into a risk appetite framework. We start by estimating a global risk factor using CDS data, and we analyse the information content in a wide set of financial indicators of the global risk factor as well as of credit risk at the level of sectors. The global risk factor is then used to evaluate the systemic and idiosyncratic components of credit risk for sectorial credit indices. A similar decomposition of credit risk is obtained for CDS issuers in the industrial and financial sectors of Europe and North America. Such decomposition can be an important tool when evaluating the diversification possibilities of credit portfolios as well as for the design of appropriate hedging strategies. It could be used by financial institutions to maintain their risk limits when taking their asset allocation decisions as well as by supervisors searching for potential systemic risk problems.

This analysis will allow us to address the following specific issues:

- What were the most systemic sectors during 2006-2012?
- What were the sectors with the largest idiosyncratic component of risk during 2006-2012?

- What are the most influential financial variables explaining credit spread fluctuations?
- How is the risk of CDS spreads decomposed among systemic risk, sector risk and idiosyncratic risk?
- Can the use of credit indices hedge a diversified CDS portfolio appropriately?
- Is there a strong geographical factor in the intra-sector analysis of the different corporate sectors?

In Chapter 4, based on the recent article "CDS de-correlation a threat to CVA hedging, traders warn" by Risk Magazine (Devasaba (2014), among others) we highlight the climate of fear prevalent throughout the industry.

"The ongoing slump in traded volumes of single-name credit default swaps (CDSs) is a "nasty side effect" of international regulatory reforms, a senior banker has claimed, raising fears that credit valuation adjustment (CVA) hedging will become increasingly difficult should the long-standing correlation between single-name and index CDS products break down. "

"As single-name volumes wither, notional outstanding in index CDS products is growing, raising fears that the long-standing correlation between CDS indexes and single-name contracts is in danger of breaking down – a consequence of tougher margin regimes and trading restrictions that have forced many credit arbitrage players out of the market."

Therefore, in Chapter 4, we estimate the basis risk between the CDS portfolio and the hedge with different indices to answer, among others, the following questions: Is the basis risk higher in North America than in Europe? Does the effectiveness of the hedge increase when we consider more than one index to hedge the portfolio? Could we improve the results using an estimation technique other than OLS? In addition to these issues we introduce the issue of hedging the Jump-to-Default risk.

Finally, in Chapter 5, the correlation among the firm's assets is one of the most important factors when calculating the capital needed to face unexpected losses of a credit portfolio under the Internal Ratings-Based approach (IRB) of the Basel Committee (2006), Basel II, and for many of the credit models in the financial industry. Unfortunately, the asset correlation is not directly observable in the market, thus we are forced to use different methods in order to estimate asset correlation.

Although the CDS market is the main reference for the credit market, we do not know about any paper stating that the use of the CDS determines the economic capital required for a loan portfolio. The main problem with this approach comes from the fact that the CDS is a risk neutral instrument. Thus, the use of the CDS for capital estimates (which is a problem based on physical probabilities instead of risk neutral probabilities), is not trivial. The economic capital estimated by CDS spreads might be a very useful alternative for portfolio managers. These estimates could provide us with relevant information regarding future systemic adverse shocks as well as an alternative tool for risk management and asset allocation.

We propose an analysis similar to Dullmann et al. (2007) but using CDS data with more industries, eleven instead of the six industries used by Dullmann, and for a more recent period, 2006-2012, where we could distinguish among the pre-crisis period, the global crisis period, and the post-crisis period. Thus, we would be able to compare these estimations against Basel II, placing these figures in the context of the regulatory capital requirement.

Global conclusions

In Chapter 1, we have reviewed the main aspects of the microstructure of the CDS market, leading to the following results:

The CDS market is concentrated in North America, Europe and Asia, most of the issuers having A or BBB ratings, with the most representative sectors being the financial, industrial and consumer services sectors. Typically, the CDS curve slope of an issuer is positive: the higher the tenor, the wider the spread, except in a stressed scenario. Also noteworthy is the usual right-skewed distribution of the CDS spread for a particular rating sector that can sometimes lead to a considerable number of “inverse observations” during a crisis period, meaning that higher ratings have wider spreads (“inversion problem”).

With respect to the restructuring event in the CDS contract, we observe that after the Big Bang Protocol there has been a higher standardisation of the CDS market, reducing the impact of the restructuring event on the CDS quotation. The Big Bang Protocol was adhered to by over 2,000 market participants and took effect on 8 April 2009, introducing the main changes:

1. Establishment of Credit Derivatives Determinations Committees (DC) for each ISDA regions to determine whether credit or succession events occurred.
2. “Auction Hardwiring”
3. Rolling Event Effective Date

In terms of the foreign exchange (FX) adjustment in CDS prices, we have shown that there is a substantial FX adjustment in CDS prices at times when the market estimates a significant adverse impact between the issuer default and the systemic risk of the local economy, as Ehlers and Schonbucher (2006) and Jankowitsch and Pichler (2005) pointed out. However, this FX adjustment is close to zero in any other time period. These conclusions should also be important for pricing loans on matters related to trade financing subject to country risk.

Regarding the impact of recovery rates on CDS, we have seen that the different standard recovery rates by regions do not influence CDS prices under normal conditions, as Duffie (1999) stated. However, we must point out the importance of taking into consideration the stochastic nature of recovery whenever bond prices are far below par value.

In Chapter 2, we have presented different econometric models to estimate sector credit curves. After an exhaustive analysis of the results from the different models, we have reached the following conclusions:

It is clear that hierarchical regression models fit the data much better than those of non-hierarchical regression. In addition, the ranking of models does not change with the sample period. However, it is obvious that during the crisis period, “fitting” errors for every model are much greater than in the rest of sample periods.

In general, we prefer the median model (50%-quantile regression) to the mean model (standard OLS regression) due to its robustness when assigning the price to a new credit asset without spread, minimizing the “inversion problem”. An additional fundamental reason to prefer the median model is the typical "right skewness" distribution of CDS spreads.

In terms of volatility, we have observed that the exponential models smooth the changes due to the rating, sector or regional factors, by estimating a less volatile spread than linear models. It is important to note that with respect to the sample criteria, we observe that the estimated series are less volatile when we do not apply any filter to the data. Our interpretation of this result is that the lowest quality rating data are less volatile than the rest of the data. This could be because the lower quality rating data tend to be fairly constant due to their low liquidity; therefore, if we include these data in the sample, we reduce the overall series volatility.

Regarding the sample criteria, we observe that all the results of this second chapter are rescaled in terms of the sum of the absolute errors and series volatility. This means that all of the econometric models presented in this chapter show the same trend, independently of the selected sample (pre-crisis, crisis or post-crisis period). Thus the rank order of the models is not altered by the selected sample criteria. For instance, the exponential models estimate a less volatile spread than the linear models independently of the selected sample. Finally, we consider the “BB Markit rating” as the best of the different analysed criteria, because it allows us to use a quality characteristic of the data, as well as all the “good” price information available daily in the market to estimate credit curves.

In Chapter 3, we provide answers for some of the questions posed in the Introduction to this thesis:

- What were the most systemic sectors during 2006-2012?

Throughout the paper, we have interpreted the first principal component calculated over the sectorial credit indices as a global risk factor. This is justified by the results we have presented as well as by the analysis in Peña and Rodriguez-Moreno.Our results show that the most systemic sector was the financial sector. The first principal component has an R-squared above 80% when explaining the variation of the Financial Sector Index for the whole period 2006-2012. These results are consistent with Moody’s [Munves (2008)] and with the proposal by the Basel Committee (2011) of a specific increase in the estimated value of asset correlation for the financial sector when calculating the level of regulatory capital required. That correlation was set at 30%, up from the previous value of 24%, while maintaining the 24% correlation for the rest of corporate sectors. According to our methodology, the industrial sector was the second most systemic sector during this period of time, possibly reflecting the impact of the global financial crisis in the real economy, since the industrial sector is distinctively dependent on financing and capital for their long-run investments, as well as the effect of the increased deterioration in the global housing market.

- What were the sectors with the largest idiosyncratic component of risk during 2006-2012?

Along the same line of reasoning, the two sectors that are the least correlated with the rest of the sectors have been the health care and technology sectors. That makes it harder to hedge credit portfolios in these sectors by taking contrary positions in some others. This outcome is not surprising, taking into account the robust growth that the health care sector is experiencing around the world. This is especially the case in developed countries (which represent the major part of our data sample) as the population of these countries is getting older, with more economic resources and a greater demand for health care services so as to achieve a better quality of life. As a consequence, the health care sector has been less influenced by the recent crisis. On the other hand, CDS returns in the technology sector have also shown low correlations with the rest of the market, possibly because of the specific nature of innovation in this industry, which has a life cycle very different from the other sectors of the economy.

- What are the most influential financial variables explaining credit spread fluctuations?

There are alternative sets of explanatory factors that can be used to explain a very significant percentage of the time fluctuations in our estimated global risk factor. This is interesting because, as we have repeatedly pointed out, such a factor represents the general evolution in the CDS spreads market. Interest rates, like the overnight LIBOR rate or its spread with the EONIA rate, the 3-month EURIBOR rate, the US Treasury 5-year rate and the slope and curvature of the term structure of US swap rates, are correlated negatively with CDS spreads. In particular, the negative correlation between CDS premia and the risk-free rate is similar to the result documented for bond yield spreads by Longstaff and Schwartz (1995) and also by Ericsson et al. (2009) when analysing the single-name CDS. This is an important result for the estimation of wrong-way risk, for which a standard assumption is to consider independence between interest rates and CDSs when searching for indicators of the risk exposure of derivatives. Hence, such assumption may lead to an underestimation of the level of risk. Another interesting empirical result is the observed positive correlation between volatility indicators like VIX, the implied volatility of the euro/dollar exchange rate and US swaption rates, and the global risk factor for the CDS market, which could be used for hedging purposes.[1] The possibility of hedging represents an interesting open question that would require further research.

- How is the risk of CDS spreads decomposed among systemic risk, sector risk and idiosyncratic risk?

We have analysed industrial and financial sectors in Europe and North America to find that, in terms of median R-squared values across issuers:

(SEE TABLE 3.16)

These results suggest the high risk involved in undiversified positions in CDS from issuers in these sectors, especially in the illiquid CDS market circumstances that arose with the financial crisis, which still exist today. They are also interesting for pricing purposes, since we could use this information to infer the credit premium of a new issuer. On the other hand, to the extent that the idiosyncratic components of risk could be uncorrel-

[1] The global risk factor also shows a natural positive association with credit indices and implicit volatility indicators for credit markets.

ated, they might allow for interesting hedging strategies, which we comment on next.

- Can the use of credit indices hedge a diversified CDS portfolio appropriately?

The answer is yes. In the light of the results of our analysis, the global risk factor displays high and positive correlations with iTraxx, in consistency with the interpretation we have given to the global risk factor. A simple regression of CDS sectorial indices with iTraxx as the only explanatory variable, other than a constant term, leads to beta estimates between 0.35 and 0.50, and R-squared coefficients between 0.20 and 0.50. An ex-post analysis of a delta-hedging strategy for a sectorial credit portfolio based on using the estimated beta to define a contrary position in the iTraxx Index, shows a substantial reduction of about 70% or more in return variance, except for the health care and technology sectors.

Furthermore, we have also shown in previous sections that the low correlation of idiosyncratic components allows for a diversified credit portfolio in any of the four sectors considered, which can be hedged following a delta-hedge strategy with the iTraxx Index. In fact, portfolios made up by firms with higher idiosyncratic components allow for quite an efficient hedge through contrary positions on the iTraxx Index, while portfolios made up by firms with lower idiosyncratic components are much harder to hedge, as expected.

These results reinforce the appropriateness of our estimates of idiosyncratic risk. They also suggest the interest of running a more detailed, ex-ante examination of the efficiency of a hedge strategy designed with the conditional second order moments estimated from a GARCH specification, possibly with some asymmetric (leverage) effects on volatility, which we leave as an issue for future research.

- Is there a strong geographical factor in the intra-sector analysis of the different corporate sectors?

A further implication from the results in the previous paragraph is that the first principal components for a given sector, estimated in different geographical regions, display similar fluctuations over time, since they are all highly correlated with the sectorial factor from Section 3.4. This suggests that the sectorial factor is more important in determining CDS spreads than the geographical region. It also implies that it might be more promising to hedge a credit position taking contrary positions in the same sector in other regions than taking a contrary position in different sectors in the same region. In fact, the sectorial risk factors for the industrial sectors in the US and Europe display a high correlation of 0.85, suggesting that sector-specific risk factors have a strong global nature, capturing elements of risk that are common to different geographical areas.

A similar observation emerges from the comparison between estimates of the sectorial components of risk for the financial sectors in Europe and North America, which are again closely related. The implication is that the sectorial factor may be much more important than the geographical factor, suggesting that firms should be thought of as members of a global sector instead of members of a particular region, there not being a noticeable diversification across the geographies in the corporate sectors. This kind of result should be interesting for financial institutions when establishing an adequate asset allocation policy for the corporate market. It seems that sectorial factors are more decisive than geographical factors in the corporate market under normal market circumstances. However, during a specific crisis in a country, the geographical factor is going to be fundamental in the CDSs of those issuers within that country. Thus, we should not forget that the geographical factors are more decisive for small/medium enterprises and for retail banking.

In Chapter 4, we have analysed the empirical risk in a CDS portfolio, defining basis risk as that induced by the imperfect correlation between the underlying single CDS contract to be replicated and the credit index contract involved in the dynamic replication strategy (e.g., iTraxx Index). Financial institutions usually prefer to hedge their CDS or CVA by trading in a credit index because of their higher liquidity and lower frictions. If changes in the price of the CDS and the price of credit index contracts were perfectly correlated, no further risk would be introduced, and one could perfectly offset any gain or loss in the position by dynamically trading in the related index contract. But we have shown that basis risk exists even in the case of a large diversified portfolio with more than seven hundred issuers, meaning that we cannot fully immunize the value of such a portfolio with a hedge based on credit index contracts and implicitly assuming that the idiosyncratic risk is offset among the different issuers in the portfolio.

We have seen that among the diverse strategies that we have applied, having accounted for the illiquidity of the market, the best strategy could be the weekly delta hedge estimate by OLS using just the three main credit indices, Europe Main iTraxx, CDX, and Japanese iTraxx. The rest of alternative strategies only slightly improve these results and they use other indices which are more illiquid, implying higher transaction costs. The Dynamic Conditional Correlation Beta estimate (DCC) turns out to be a more volatile estimate, implying the higher entrance and exit costs of continuously adjusting the hedge. The DCC estimate might be optimal in a situation with very high volatility, but it performs almost equally to OLS over the course of an economic cycle.

Another important result in this chapter is that the Jump-to-Default cannot be ignored as the use of delta hedging is partial hedging and its effectiveness is predicated by continually adjusting the hedge ratio. Therefore, if a single issuer jumped to default, we would not be able to adjust the hedge ratio appropriately, and the defaulted credit exposure would not be fully covered, resulting in a loss. It is still an open question whether we can calibrate a jump model to evaluate the credit index hedge over the Jump-to-Default of issuers that are not included in that credit index.

Hence, it seems clear that when pricing credit derivatives, we should charge some basis points reflecting unheadgeable risk. A good starting point might be to measure the losses in basis points as an extra charge to include in the price of the derivatives depending on the proxy portfolio and adjusting by maturity. From the point of view of regulators, we could think of using a historical percentile as a lower bound on the historical basis risk that should be added in terms of capital, and monitor this risk in financial institutions in order to prevent future problems.

In Chapter 5, we have shown that the four models considered (Market, Sector, Individual Sector and Sector Market) have the same trend in terms of VaR, with some small differences. In our opinion, our results suggest that the use of a one-factor model can be a good representation of the problem, due to the high inter-sector correlation during our 2006-2012 sample period. If that were not the case, the different models might have rather distinct implications.

On the other hand, we have argued that the main reason for the increase in Credit VaR over time has been the growing intra-sector and inter-sector correlations among credit markets. Also worth noting is the increase in the average probability of default of the issuers provided by the external rating. In addition to this, we show that there were signs in the credit market that the financial sector probably did not introduce into their internal risk models in order to manage their risk during the crisis.

Finally, as a general reflection, it would be interesting to consider a new calibration for the Basel II functional representation of the capital requirement in the banking book that could better reflect credit market expectations. The credit derivative market has a strong speculative component and it is very illiquid. But it is also clear that this market reflects quite well the specific economic circumstances of each moment, and the CDS market will continue to be a key component of future credit markets. In order to have a robust credit market, we need to have the possibility of hedging the credit exposure against any counterparty. In the absence of a market where we can buy protection for credit, the price of credit will be unnecessarily high.

Chapter 1

Introduction: Microstructure of CDS market

1.1 Introduction

In this first chapter, we study the most relevant aspects of the microstructure of the CDS market in terms of pricing in order to have a clear idea of how this market works. Thus, perhaps it is not so relevant for the financial literature, but we consider it to be the starting point for establishing a solid base for the rest of the chapters in order to carry out the different empirical studies of this thesis. Given the aim of the next chapter, the determination of credit spread, the first question is: Could we aggregate the several single-name CDSs without considering the currency of the CDS contract? Similarly, how do the restructuring clauses affect the CDS quotations? And of course, what filters can be applied to the data quality? All these questions will be analysed throughout the first section of this chapter, as they are key to building the credit spread models.

This chapter is divided into eight sections in addition to this one. In Section 1.2 we define a CDS contract. In Section 1.3 we follow with a description of the Markit database that we will use in the rest of the chapters. In Section 1.5 we briefly describe the CDS spread distribution by sector, rating and region to have an initial idea of the main features of the CDS distribution. Section 1.7 deals with the analysis of the restructuring event in the CDS price. Section 1.6 focuses on the FX adjustment in the CDS price. In Section 1.7 we review the recovery of the CDS market to have a better understanding of this assumption of the market and its implications. In Section 1.8 we start to analyse the implications of the use of some filters for the data quality of the CDS market in order to see if this assumption is relevant or not. Finally, in Section 1.9 we propose a criterion for data aggregation that we will use in the rest of the chapters.

1.2 CDS definition

A CDS contract involves the transfer of the credit risk of an underlying agreement like municipal bonds, emerging market bonds, mortgage-backed securities, or corporate debt between two parties, Figure 1.1. It provides the buyer (who may also own the underlying credit) with protection against default or another negative credit event. In the event of default, the buyer of the CDS receives compensation, usually the face value of the loan, and the seller of the CDS takes possession of the defaulted loan. A default is often referred to as a "credit event" and includes events such as failure to pay, restructuring and bankruptcy, or even a drop in the borrower's credit rating. The exact nature of a credit event varies from contract to contract and is defined in the specific agreement between two parties [JP Morgan (1999)].

The seller of the contract assumes the credit risk that the buyer does not wish to maintain in exchange for a periodic protection fee similar to an insurance premium, and is forced to pay only if a defined credit event occurs. It is important to note that the CDS contract is not actually tied to a bond, but instead references it. For this reason, the bond involved in the transaction is the so-called "reference obligation." A contract can reference a single credit, or multiple credits. If there is no credit event or no default, the seller of protection receives the periodic fee from the buyer, and profits if the reference entity's debt remains good through the life of the contract and no payoff takes place.

In case of a credit event, the party that sold the credit protection, who has assumed the credit risk, must deliver the value of principal and interest payments that the reference bond would have paid to the protection buyer. With the reference bonds still having some low residual value, the protection buyer must in turn deliver either the current cash value of the referenced bonds or the actual bonds to the protection seller, depending on the terms agreed upon at the onset of the contract. If there are more CDS contracts outstanding than bonds in existence, a protocol exists to hold a credit event auction; the payment received in such cases is usually substantially less than the face value of the loan.

1.3 Introduction to Markit database

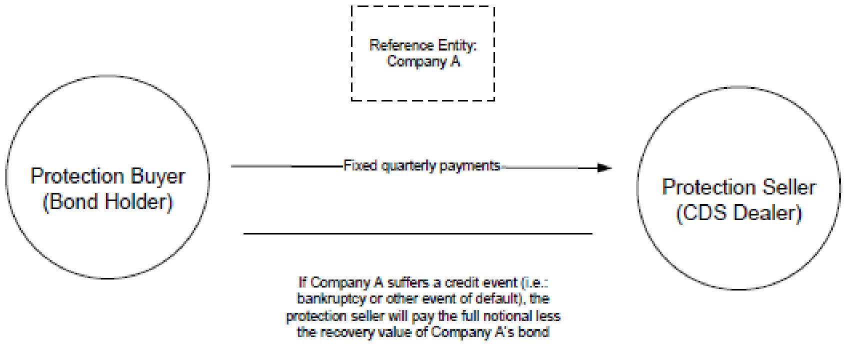
The database that we have used for this thesis is provided by Markit, the main source of CDS prices [Markit (2008) and Markit (2012)]. The several fields that we have selected are:

- Ticker gives us information about the key name of the issuer.
- Tier gives us information about the type of debt that we have to deliver in the event of a default. We distinguish the following:

SEDCOM Secured Debt (Corporate/Financial)

SNRFOR Senior Unsecured Debt (Corporate/Financial)

Figure 1.1: CDS payments



SOVEREIGN Debt (Government)

SUBLT2 Subordinated or Lower Tier 2 Debt (Banks)

JRSUBUT2 Junior Subordinated or Upper Tier 2 Debt (Banks)

PREFT1 Preference Shares, or Tier 1 Capital (Banks)

- Ccy represents the currency that we use to make the payment in the CDS contract in case of a credit event. A permitted currency includes the currencies of the G7 or an OECD member with a AAA or equivalent rating.

- DocClause defines the type of default event that is under the CDS contract. Depending on the geographical area and counterparty, there will normally be different standard clauses:

CR (Full Restructuring). The buyer can deliver a bond of the reference entity with a maximum maturity of 30 years after the default event date. It represents the standard clause for the sovereign CDS contract.

MM (Modified-Modified). The buyer can deliver a bond of the reference entity with a maximum maturity of five years for the restructuring event after the default event date. In case of another type of default event, the buyer can deliver a bond of the reference entity with a maximum maturity of 2.5 years after the default event date.

MR (Modified-Restructuring). The buyer can deliver a bond of the reference entity with a maximum maturity of 2.5 years after the default event date.

XR (No Restructuring). In this case, the restructuring is not considered as an event of default. Nowadays XR is the standard clause in the USA. Refer to Section 1.5 for additional details.

- Markit provides us with the information of the different CDS spreads with different tenors: 6M, 1Y, 2Y, 3Y, 4Y, 5Y, 7Y, 10Y, 15Y, 20Y and 30Y. The most liquid CDS is the 5-year contract. All these prices are composite, that is, they are average prices for a restructuring event and currency for an issuer provided by different financial institutions.
- Recovery represents the standard market recovery for each geographical region.
- Average Rating is the mean rating provided by the rating agencies with a short rating scale, being AAA, AA, A, BBB, BB, B, CCC and D.
- Sector is based on the ICB criteria, (Industry Classification Benchmark), which distinguishes four levels: industry, supra-sector, sector and subsector. In this case, Markit works with the industry level, differentiating eleven industries:
- *Basic materials, consumer goods, consumer services, energy, financials, government (Markit category), health care, industrials, technology, telecommunication services and utilities.*
- By regions, we have thirteen different regions:
- *Africa, Asia, Caribbean, Eastern Europe (E.Eur), Europe, India, Latin America (Lat.Amer), Middle East, North America (N.Amer), Oceania, Offshore, Pacific and Supranational (Supra).*
- CompositeDepth5y gives information about the number of price contributors to the 5-year CDS contract. The higher the number of contributors, the more liquid the contract.
- CompositeCurveRating tells us about the data quality average of the different CDS contracts for a particular issuer. Markit has their own methodology to assign this rating. These ratings can be AAA, AA, A, BBB, BB, B and CCC. It is also possible to find this quality rating for a single tenor CDS contract of the issuer. This information has been available since 1 January 2006.

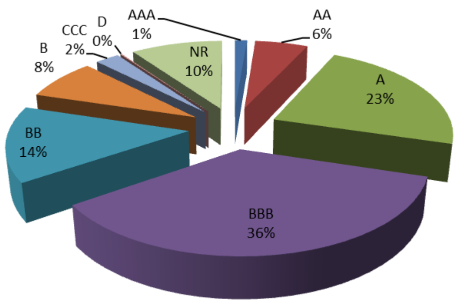
1.4 First outlook for CDS by rating, sector and region

In this section, we analyse in depth our understanding of the CDS market by studying the following questions:

Which are the most common ratings among CDS issuers? Which are the sectors with the most CDS issuers? Which are the most representative regions in the CDS market? Which is the usual type of CDS distribution for a determined rating-sector? Is it possible to observe an “inverted” premium risk (worse ratings imply better spreads) in the market?

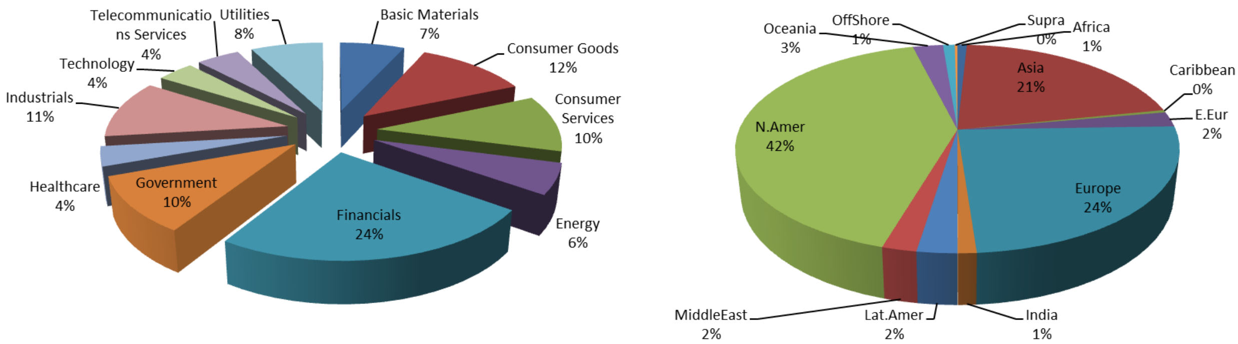
We analyse the distribution of CDS by ratings, sectors and regions for a particular day, 31 January 2012 (see Figures 1.2 and 1.3). We see that most of the issuers have “BBB” or “A” ratings. The most representative sectors are financials, consumer services and industrials. Finally, it makes sense that the main regions are: North America, Europe and Asia. Although we show the CDS distribution by rating, sector, and region for a particular day, these distributions are relatively stable through time.

Figure 1.2: CDS market by ratings on 31 January 2012



Note: CDS market share by rating classification on 31 January 2012 using Markit database.

Figure 1.3: CDS market by sectors (right graph) and CDS market by regions on 31 January 2012

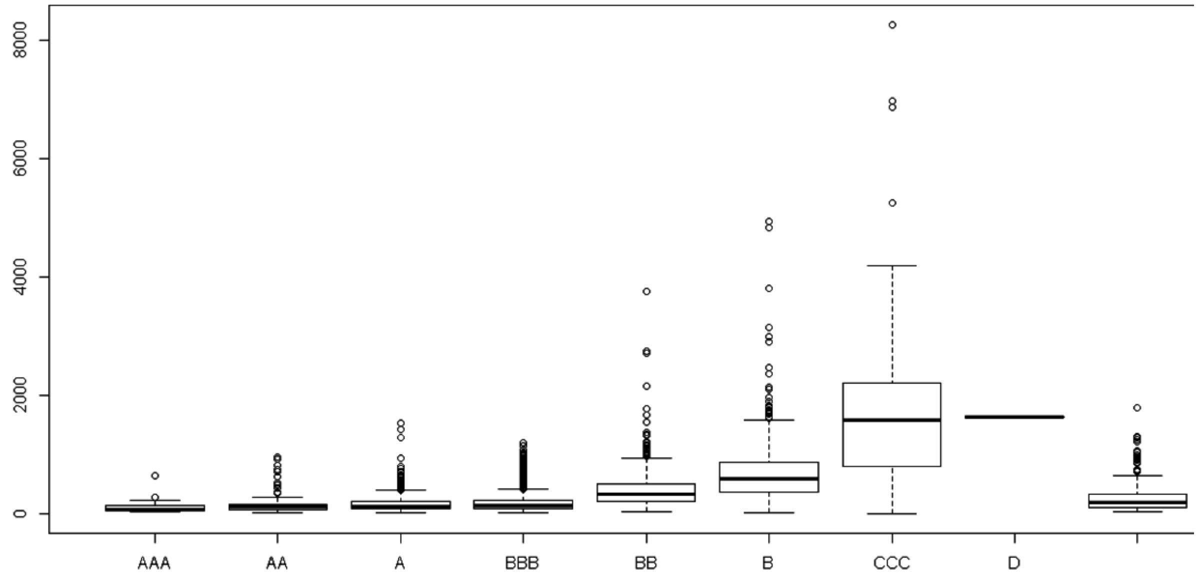


Note: CDS market share by Industry Classification Benchmark provided by Markit (right graph) and CDS market share by regions on 31 January 2012, using Markit database.

First outlook for CDS by rating

Analysing the premium risk for all the ratings in Figure 1.4 and Table 1.1 (we select the senior 5-year CDS contract as it is the most liquid contract), it can be seen immediately that market discriminates clearly by the rating. This means that, the better the rating, the lower the spread. The last class represents those issuers without a rating. We focus on the spreads that mainly appear in dataset (0%-15%), including the sector component in Figure 1.5. It can be observed that the market is more volatile for “high yield”ratings, significant differences existing across sectors.

Figure 1.4: CDS spread (basis points) box-plot by rating on 31 January 2012



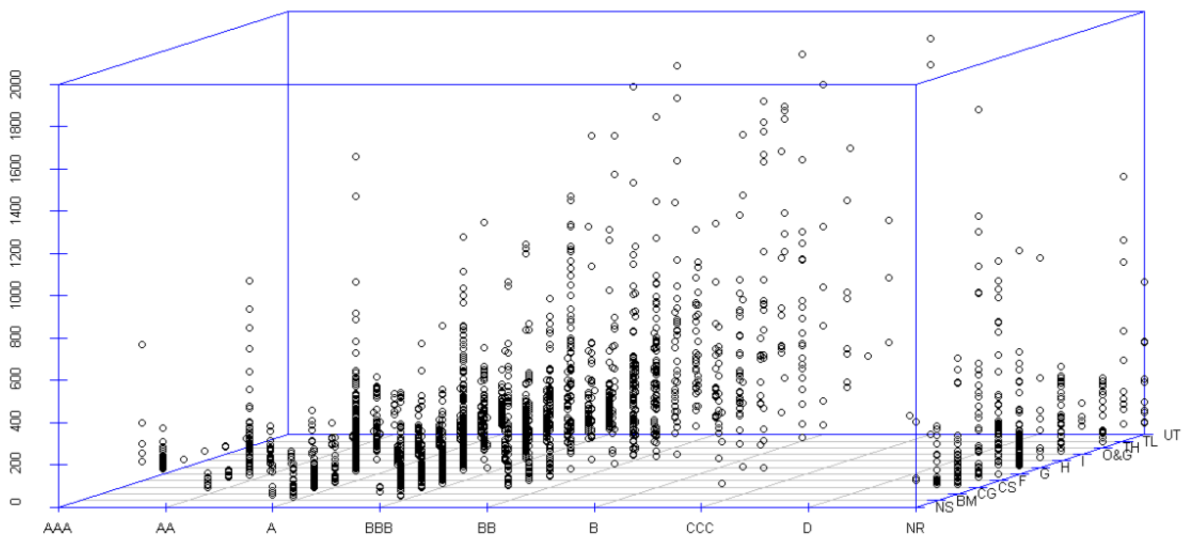
Note: CDS spread (basis points) box-plot by rating on 31 January 2012 using Markit database. The last box-plot corresponds to those issuers with no rating.

Table 1.1: CDS spread (basis points) by rating . Main statistics on 31 January 2012

Rating	Min.	1st Qu	Median	Mean	3rd Qu	Max.	NA's
AAA	25.2	43.0	67.2	133.6	127.1	644.6	
AA	13.1	59.9	108.3	136.0	158.0	957.5	
A	14.8	74.6	118.4	157.8	199.5	1534.0	
BBB	10.8	88.7	141.1	181.6	219.7	1194.0	
BB	21.9	199.9	320.1	392.4	503.3	3763.0	7
B	17.7	366.5	578.4	724.0	861.3	4932.0	1
CCC	100.0	794.6	1581.0	1636.0	2170.0	8260.0	37
D	1633.0	1633.0	1633.0	1633.0	1633.0	1633.0	8
Not Rated	30.2	106.2	179.0	280.1	330.9	1785.0	43

Note: Min: Minimum, 1st Qu: First quartile, 3rd Qu: Third Quartile, Max: Maximum. NA's: Not Available information. CDS spread (basis points) on 31 January 2012 using Markit database.

Figure 1.5: CDS distribution (basis points) by rating and sector on 31 January 2012



Note: NR: Not rated, NS: Without sector, BM: Basic materials, CG: Consumer goods, CS: Consumer services, F: Financials, G: Government, H: Health care, I: Industrials, O&G: Energy , TH: Technology, TL:Telecommunication services and UT: Utilities.

First outlook for CDS by sector

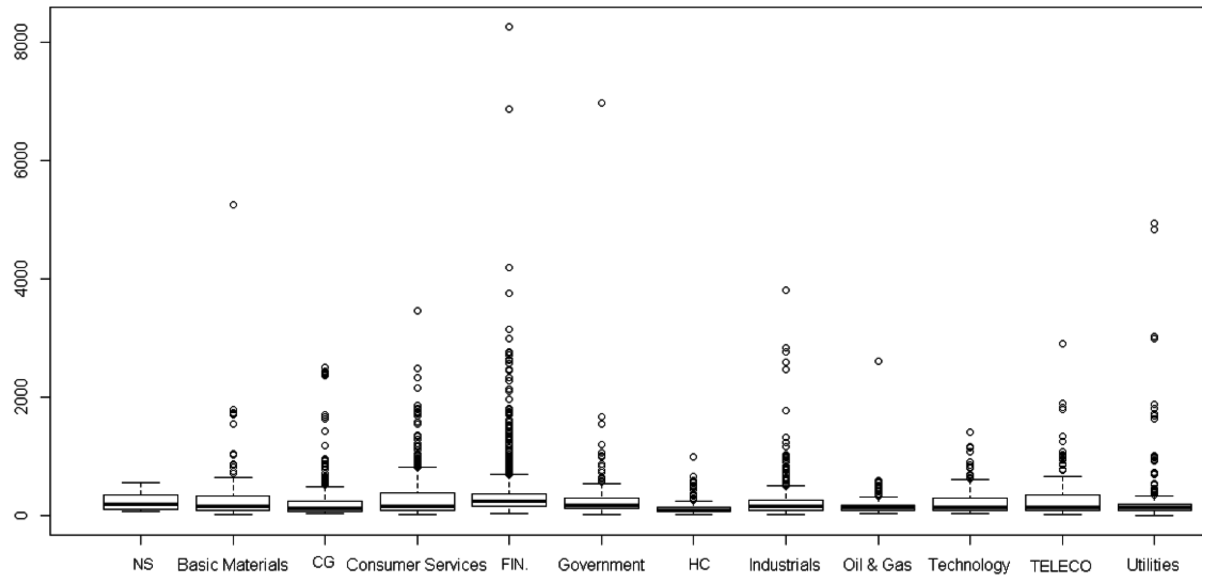
Now, we describe the CDS market by sector, representing the box-plot and the main statistics on 31 January 2012 (Figure 1.6), Table 1.2 and Figure 1.7. During the recent crisis, the most affected sectors are the financial sector and the government sector. On the other hand, in the high-yield sectors we see that the industrial (which includes the real estate sector) and the consumer services sectors have been the most affected ones by the crisis. It must be taken into account that this last sector is very diverse and depends on the region where it is located.

Table 1.2: CDS spread (basis points) by sector. Main statistics on 31 January 2012

Sector	Min.	1stQu.	Median	Mean	3rdQu.	Max.	NA's
Without sector	58.0	90.1	184.4	204.3	342.1	553.2	
Basic materials	17.4	76.3	148.0	245.4	319.4	5254.0	5
Consumer goods	27.8	71.9	118.8	221.9	244.0	2493.0	6
Consumer services	17.6	78.8	153.0	295.8	370.5	3458.0	13
Financials	27.9	152.7	229.2	358.4	368.0	8260.0	20
Government	13.1	118.0	169.6	241.3	290.7	6972.0	
Health care	14.8	55.9	78.5	134.5	132.8	991.7	
Industrials	11.8	80.4	142.7	232.3	248.2	3800.0	
Energy	37.4	80.4	135.8	161.6	176.0	2599.0	
Technology	22.5	75.9	139.9	248.9	287.4	1401.0	
Telecommunication services	10.8	81.0	129.4	280.0	347.4	2907.0	
Utilities	1.0	86.4	129.9	248.9	185.9	4932.0	9

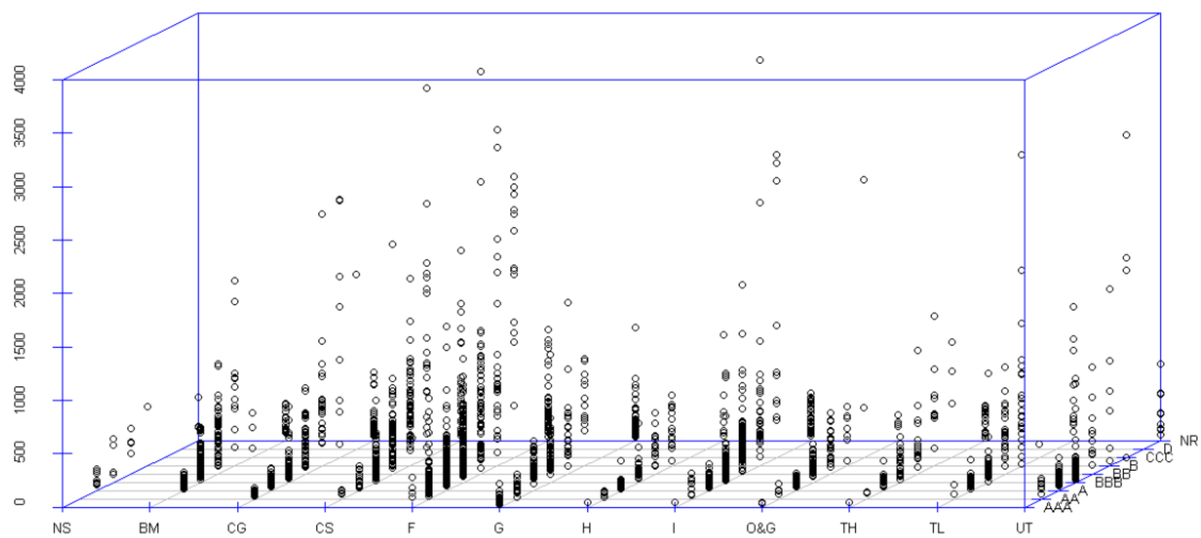
Note: Min: Minimum, 1st Qu: First quartile, 3rd Qu: Third Quartile, Max: Maximum. NA's: Not Available information. CDS spread (basis points) on 31 January 2012 using Markit database.

Figure 1.6: CDS spread (basis points) box-plot by sector on 31 January 2012



Note: NS: Without sector, CG: Consumer goods, FIN: Financial, HC: Health care, Oil & Gas: Energy, TELECO: Telecommunication services. CDS spread (basis points) by sector on 31 January 2012 using Markit database.

Figure 1.7: CDS distribution (basis points) by sector and rating on 31 January 2012

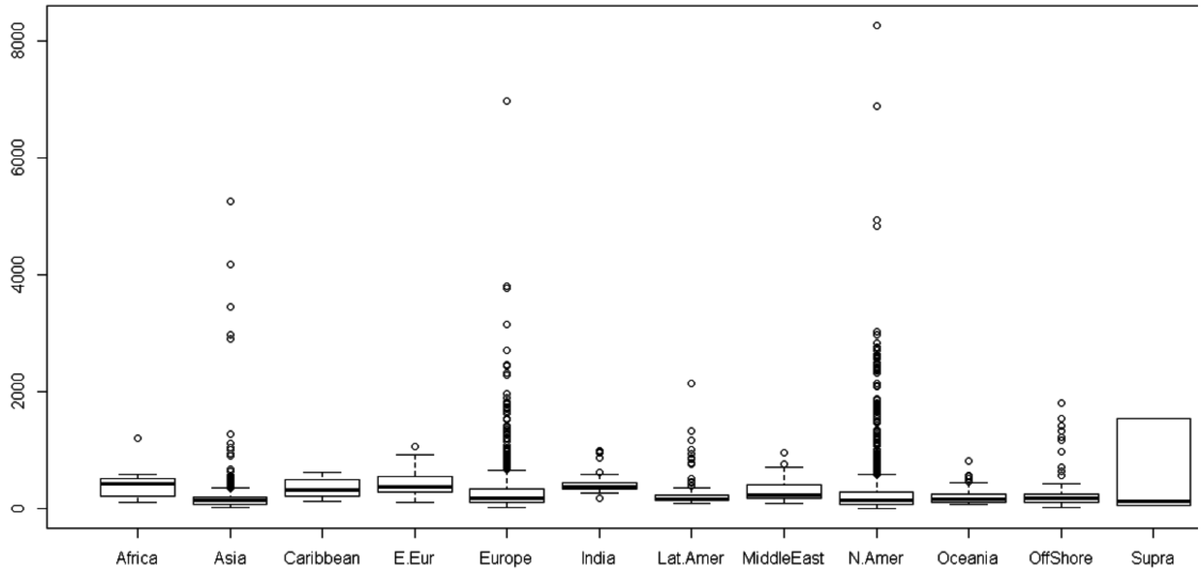


Note: NR: Not rated, NS: Without sector, BM: Basic materials, CG: Consumer goods, CS: Consumer services, F: Financials, G: Government, H: Health care, I: Industrials, O&G: Energy , TH: Technology, TL:Telecommunication services and UT: Utilities.

First outlook for CDS by region

By region, we observe that the principal CDS markets are placed in North America, Europe, Asia (mainly in Japan) and Oceania (Figure 1.8 and Table 1.3). At the same time, North America and Europe show a greater dispersion due to the higher number of issuers in these regions, covering a wide spectrum of ratings and sectors .Such dispersion in CDS spreads exists even for the same rating, indicating that the sector component can be very influential in the CDS spread. According to the following table, if we focus on the senior 5-year CDS contract by region, we clearly observe that, in general, the market premium risks in Asia are lower than in other regions.

Figure 1.8: CDS (basis points) box-plot by region on 31 January 2012



Note: E.Eur: Eastern Europe, Lat.Amer: Latin America, MiddleEast: Middle East, N.Amer: North America. CDS spread (basis points) by region on 31 January 2012 using Markit database.

Table 1.3: CDS spread (basis points) by region. Main statistics on 31 January 2012

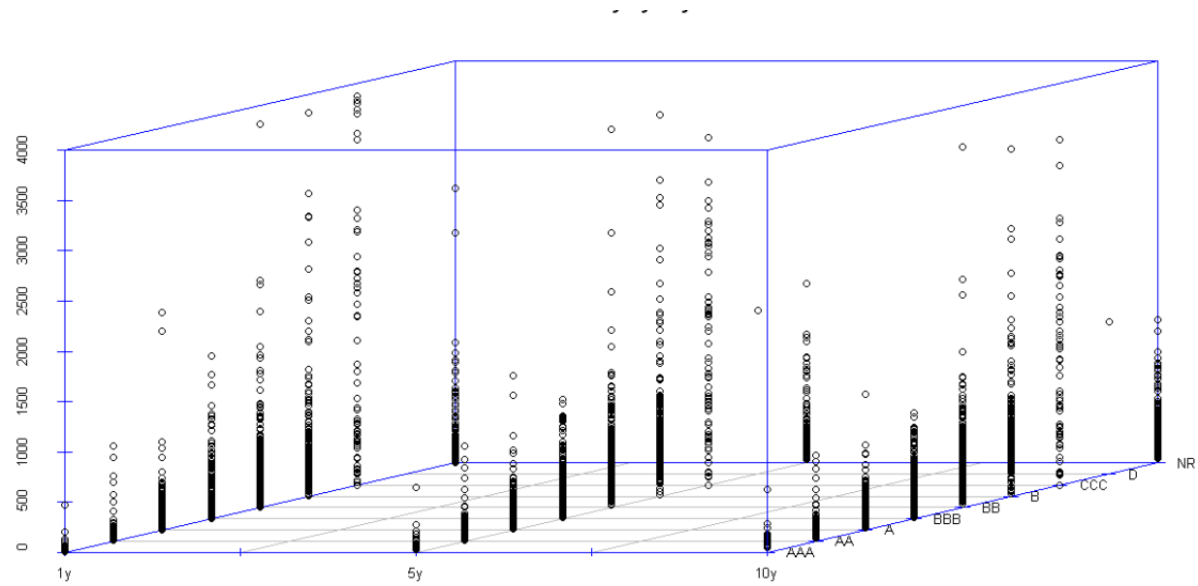
Region	Min.	1stQu.	Median	Mean	3rdQu.	Max.	NA's
NA	101.5	217.8	422.2	398.5	512.3	1210.0	
Asia	24.2	79.5	143.0	187.5	189.3	5254.0	
Caribbean	118.4	221.0	313.5	352.0	492.9	628.8	
E.Eur	109.9	278.1	378.5	433.0	557.3	1059.0	
Europe	24.1	108.7	174.2	285.0	331.4	6972.0	17
India	175.4	340.1	372.2	430.9	442.4	990.5	
Lat.Amer	91.0	145.5	160.4	293.1	240.6	2145.0	
Middle East	86.8	179.4	228.4	302.5	406.5	960.0	
N.Amer	1.0	76.9	138.9	272.0	281.4	8260.0	36
Oceania	76.2	113.8	157.5	198.8	250.5	812.0	
Offshore	28.2	113.2	180.2	277.7	250.7	1811.0	
Supra	52.7	62.3	127.1	598.3	1538.0	1539.0	

Note: Min: Minimum, 1st Qu: First quartile, 3rd Qu: Third Quartile, Max: Maximum. NA's: Not Available information. CDS spread (basis points) on 31 January 2012 using Markit database.

First outlook for CDS by tenor

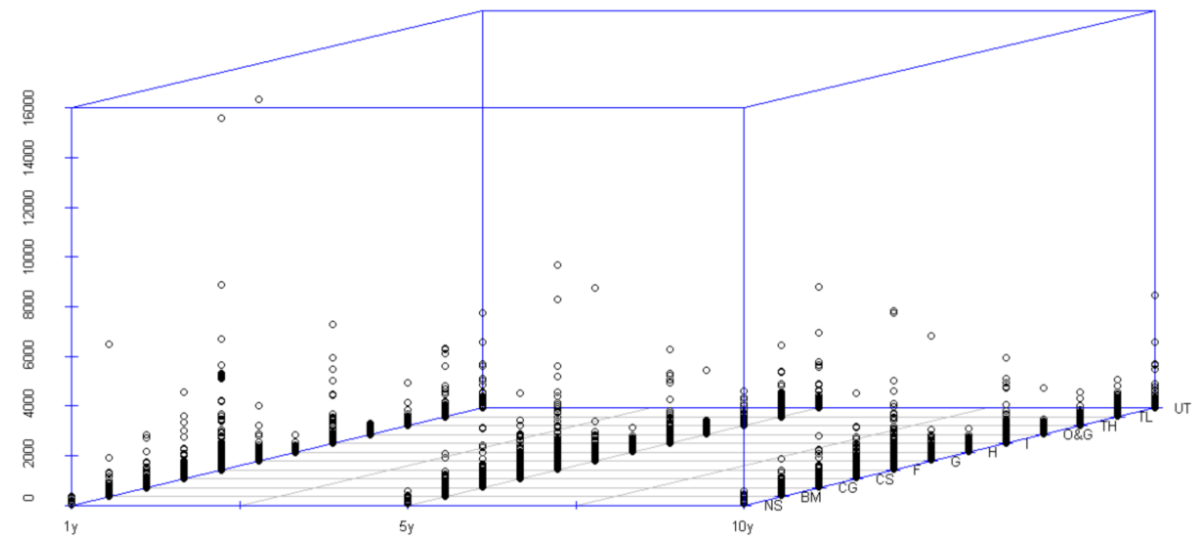
Generally, the slope of the CDS curve for a particular investment grade issuer is positive, meaning that the higher the tenor, the wider the spread (Figures 1.9 and 1.10). However, the slope of the CDS curve for the high yield issuer is typically flat, even negative in some cases. On the other hand, by sectors, we have similar outcomes, we observe that sectors that are more stressed have flattened slopes or even negative ones. Lastly, for those sectors that present normal market conditions, the slope is typically positive.

Figure 1.9: CDS distribution (basis points) by tenor and rating on 31 January 2012



Note: NR: Not Rated, 1y: 1-year tenor, 5y: 5-year tenor, 10y: 10-year tenor.

Figure 1.10: CDS distribution (basis points) by tenor and sector on 31 January 2012



Note: NR: Not Rated, NS: Without Sector, BM: Basic materials, CG: Consumer goods, CS: Consumer services, F: Financials, G: Government, H: Health care, I: Industrials, O&G: Energy , TH: Technology, TL:Telecommunication services and UT: Utilities.

First outlook for CDS by rating sector

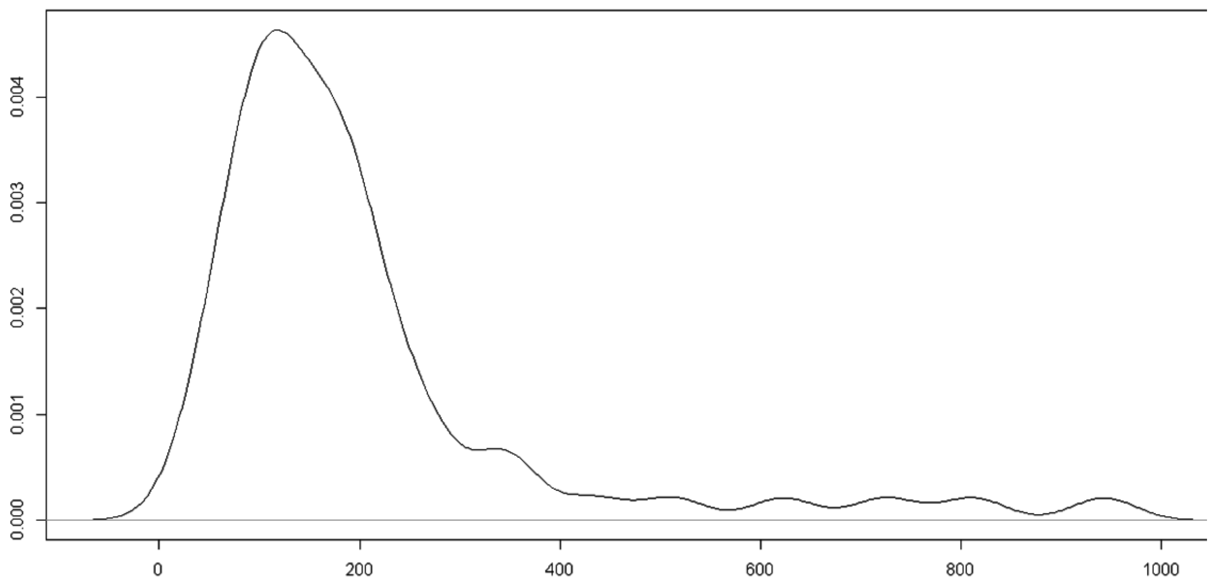
Now we analyse CDS data for a selected sample sorted by ratings and sectors. In this case, we have chosen the AA financial and BBB industrial sectors because of their representativeness (Table 1.4 and Figures 1.11 and 1.12). As the financial literature shows [see, for example, Munves et al. (2007)], the CDS distributions by rating sector are usually right-skewed; that is, the heavy tail is on the right side.

Table 1.4: AA financial and BBB industrial CDS spreads (basis points). Main statistics on 31 January 2012

Sector	Min.	1stQu.	Median	Mean	3rdQu.	Max.
AA financial	27.9	116.9	157.0	196.7	215.9	957.5
BBB industrial	11.7	86.0	128.7	156.6	180.1	1023.0

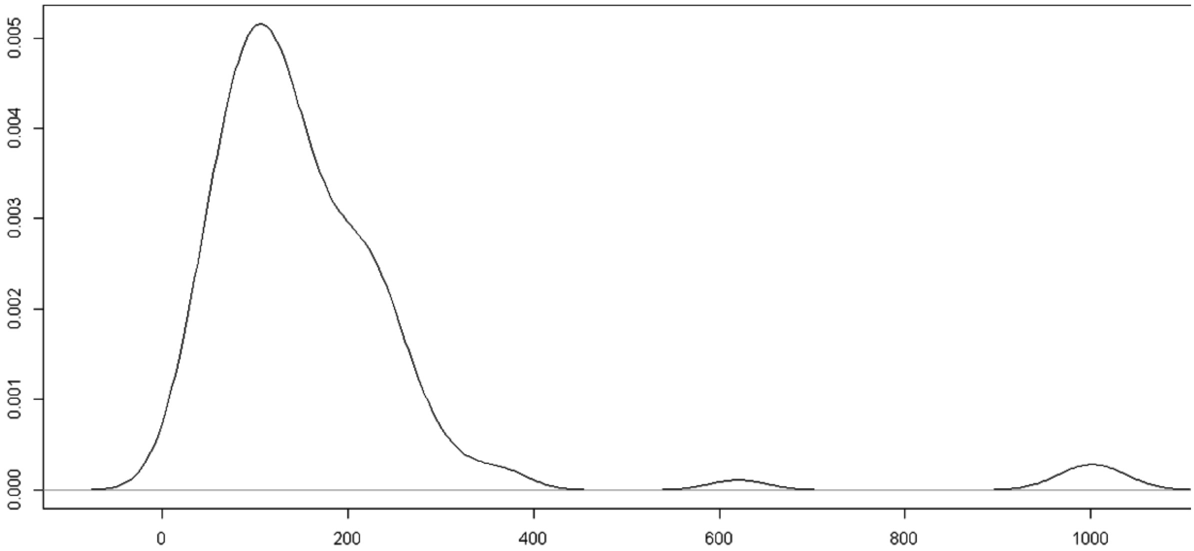
Note: Min: Minimum, 1stQu: First quartile, 3rdQu: Third Quartile, Max: Maximum.
CDS spread (basis points) on 31 January 2012 using Markit database.

Figure 1.11: AA financial CDS spread (basis points) density function on 31 January 2012



Note: X axis: Spread CDS in basis points. Y axis: Density

Figure 1.12: BBB industrial CDS spread (basis points) density function on 31 January 2012



Note: X axis: Spread CDS basis points. Y axis: Density

First outlook for temporal CDS distribution by rating sector

For this first outlook, we consider the dataset from January 2008 to April 2010. Analysing the global mean of CDS by rating, we observe a considerable number of "inverse observations"; this means that higher rating have wider spreads, Figure . This fact has more relevance if we observe the average CDS by ratings for a particular sector, as we can see in Figure 1.13. An alternative option to solve this "inversion problem", having the skew to the right of the distribution of the CDSs is to use the median, which is more robust in the presence of outliers in the distribution than the mean, thus reducing the "inversion problem" observed in the market (see Figure 1.14). This fact could be explained by factors like the stress of the market, the illiquidity of the market, or a high speculative component in the CDS market in the short run. We propose a solution for this problem in Subsection 2.5.7.

Figure 1.13: Global mean CDS (right graph), and industrial average CDS (left graph) by rating. January 2008 to April 2011

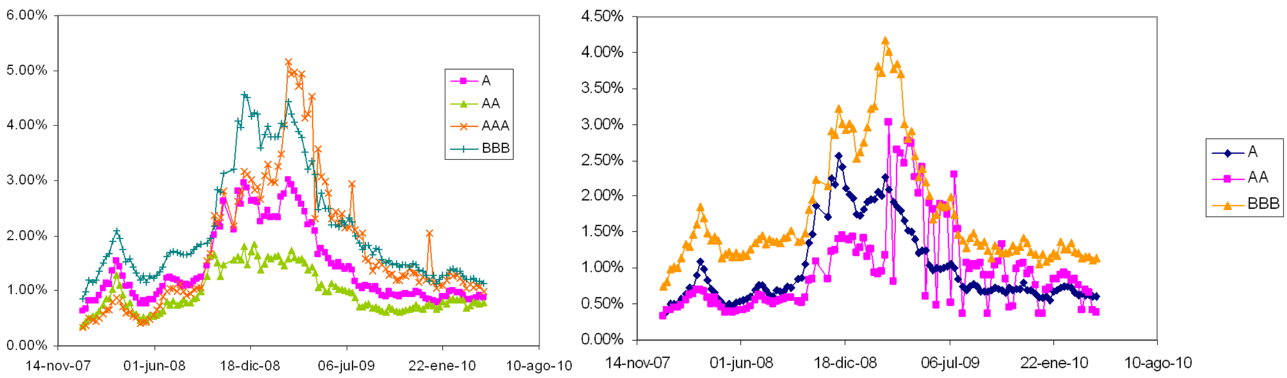
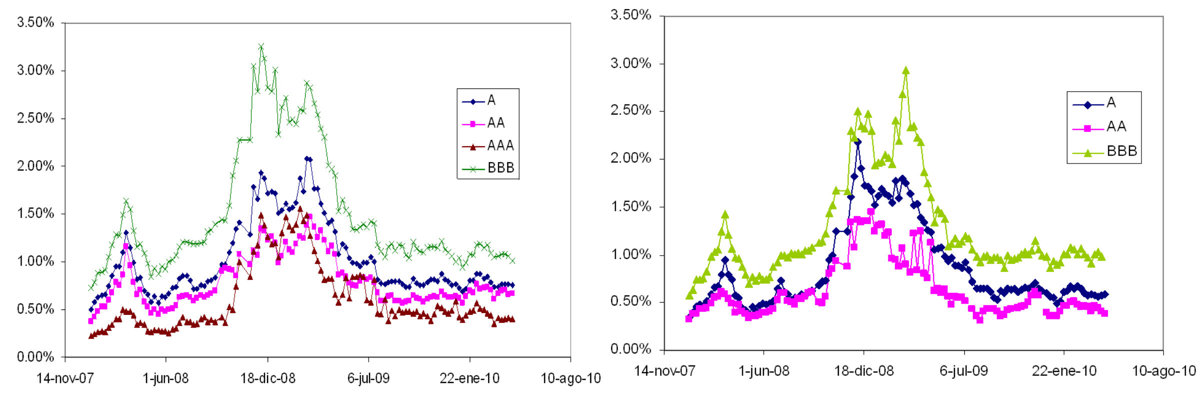


Figure 1.14: Global median CDS(right graph), and industrial median CDS (left graph) by rating. January 2008 to April 2011



1.5 Outlook for the restructuring event in the CDS contract

What is the definition of a restructuring event? Why are there so many definitions of the restructuring event depending on the type of counterparty and the region? What changes were introduced by Big Bang Protocol in 2009? What is the influence of the restructuring event in the CDS quotation? These are some of the questions that we will focus on this section.

1.5.1 Introduction

The definitions of the different restructuring event clauses included in the CDS contract are the following:

- **Full Restructuring (CR)**. In this case, we are protected against the restructuring event, and the default event. This type of clause is the broadest definition for the delivery of bonds with a maximum tenor of 30 years after the restructuring date in a default event. Under this clause, any restructuring event is considered a credit event. This is the standard clause outside of Europe and North America. Similarly, it is the standard for sovereign CDSs because the restructuring event is included. This event is the classical way for countries to avoid or delay payments.

- **Modified Modified Restructuring (MM)**. Restructuring is defined as a credit event and deliverable obligations limited to debt maturing in up to 60 months, (30 months for the rest of the credit events). This clause is standard for Europe.

- **Modified Restructuring (MR)**. Restructuring is defined as a credit event and deliverable obligations are limited to debt maturing in up to 30 months, or even less if the maximum maturity of the restructured debt is lower than those 30 months. Additionally, it is necessary for the deliverable obligations to be fully transferable, which is not the standard for the loan market.

- **No Restructuring (XR)**. Finally, with this clause, we are protected against the default events, but a restructuring event is not considered as a credit event. This was the standard clause for “High Yield” companies in North America before the CDS Big Bang Protocol. In 2009 with the introduction of the CDS Big Bang Protocol, this clause became standard for any company in North America.

The different definitions about the restructuring event were gradually introduced in response to market needs, Markit (2009a).

In 1991 the ISDA definition required the obligation to be “materially less favourable” to holders introducing the concept of the materiality test for CDSs.

In 1999 ISDA defined the Credit Derivatives and listed the five cases that define a Restructuring event. The contracts that include these definitions are known as Full Restructuring or Old R. The five cases are listed here:

1. Reduction in the amount of principal at maturity or redemption dates.
2. Reduction in the rate or amount of interest payable or in the overall number of interest payment periods.
3. Any change in the seniority or ranking of payments of any obligation, causing the subordination to any other obligation.
4. Postponement or deferral of a date for payment of interest, accrual, or principal.
5. Any change in the currency conversion of the interest payment or principal to any currency that is not a permitted currency.

However, restructuring events vary significantly from one credit event to another. The softest credit event would be a change in the payment currency. In general, this fact has a small impact for the bond owner except in specific circumstances. The hardest restructuring event would be a reduction of principal or interest payment. It would be very close to the definition of failure payment or default, and it would imply a big pricing impact on the issuer’s debt.

For instance, in the Conseco Finance restructuring event, maturity extension of the short run bank loans triggered the restructuring event. At the time, longer maturity bonds quoted with a deep discount compared to bank loans. Protection buyers triggered their trades and delivered their distressed bonds, taking advantage of this situation, while the general view of financial analysts was that the restructuring event was soft.

Thus, the question is: how material does a restructuring have to be in order to constitute a restructuring event? While it is possible to give a legal definition for the restructuring event, it is more difficult to define the concept of material restructuring. For this reason, market participants prefer to define clear rules to specify the deliverable obligations, depending on whether a protection buyer or seller triggers, instead of defining the difficult concept of material restructuring.

After a restructuring event, the bonds which are not in default, generally longer dated bonds quote cheaper than shorter dated bonds. Thus, buyers have a maturity limit when delivering bonds, in order to constrain their protection, as buyers could deliver longer dated bonds, which are cheaper than the restructured bonds, taking into account that the restructured bonds were the ones affected.

On the other hand, if it is the seller who triggers the trade, then the seller will have an incentive to do so. But without any restrictions in the deliverable bonds, the unintended gain for the seller is limited. For example, in a context of low rates, it is possible for the bonds to trade above par. Thus, in case of an immaterial restructuring event, the buyer is forced to deliver bonds which trade above par, receiving the par value. Therefore, to avoid this situation, there is no limitation for the buyer to deliver any bond if the seller triggers it.

The case of Conseco Inc. was the reason to develop in more detail the previous definition of Modified Restructuring. Europe was more concerned than the USA about the Modified Restructuring clause because it was very limited. For this reason, Europe developed Modified Modified Restructuring, as the maturities of corporate bonds were longer than in the past.

In Figure 1.15 Markit summarises the different clauses, the deliverable bonds under each clause, and the transferability of these obligations.

Figure 1.15: Restrictions on deliverable obligations for restructuring events

	Old R	Mod R	Mod Mod R	No-R
Maximum Maturity	Maximum maturity up to 30 years beyond Restructuring Date	Restructuring Maturity Limitation (earlier of 30 months from Restructuring Date and latest final maturity date of any Restructured Bond or Loan)	Modified Restructuring Maturity Limitation (later of maturity or 60 months from Restructuring Date for restructured obligations, 30 months from Restructuring Date for all other obligations)	N/A
Transferability	No restrictions	Must be Fully Transferable	Must be Conditionally Transferable	N/A

Source: Markit

1.5.2 Big Bang Protocol

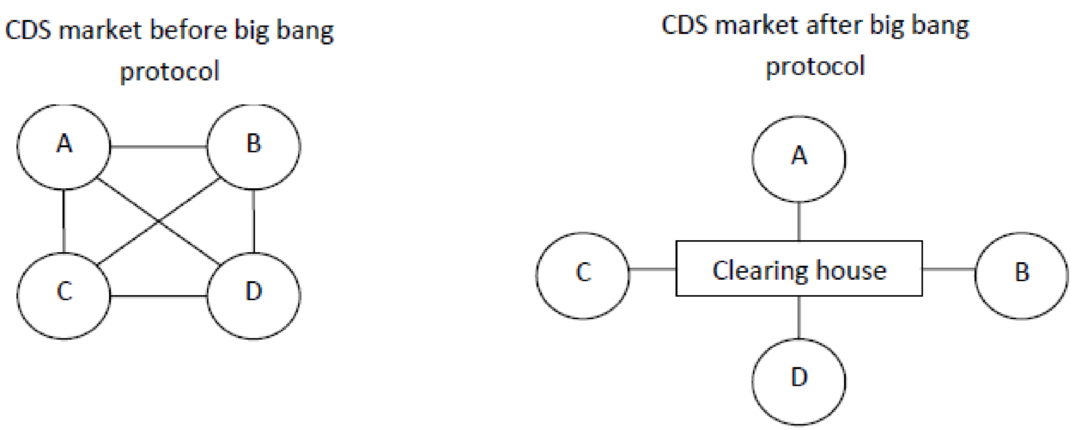
By the Big Bang Protocol, regulators want to standardize CDS contracts so that they could be netted at an early stage. The aim is to allow contracts to nett at time zero. Figure 1.16 shows how markets traded before the "bang" protocols and how markets trade today [Markit (2009d), Markit (2009a) and Markit (2009b)].

The Big Bang Protocol was adhered to by over 2,000 market participants and took effect on 8 April 2009. These were the main changes introduced:

1. Establishment of Credit Derivatives Determinations Committees (DC) for each ISDA regions to determine of whether credit or succession events occurred.
2. "Auction Hardwiring"
3. Rolling Event Effective Date

According to the Big Bang Protocol, there are different CDs for each ISDA region: the Americas, Asia excluding

Figure 1.16: Big Bang Protocol



Source: Markit

Japan, Japan, Australia-New Zealand and EMEA. The most important responsibility is to decide if a credit event happened, the type and date. This means that a credit event will be determined by the Committee instead of the two involved parties as in the past. The CDs will make decisions on the acceptable deliverable obligations and any substitute reference obligations if applicable. Thus, the new protocol facilitates central clearing, as the default event will be the same for all the reference contracts.

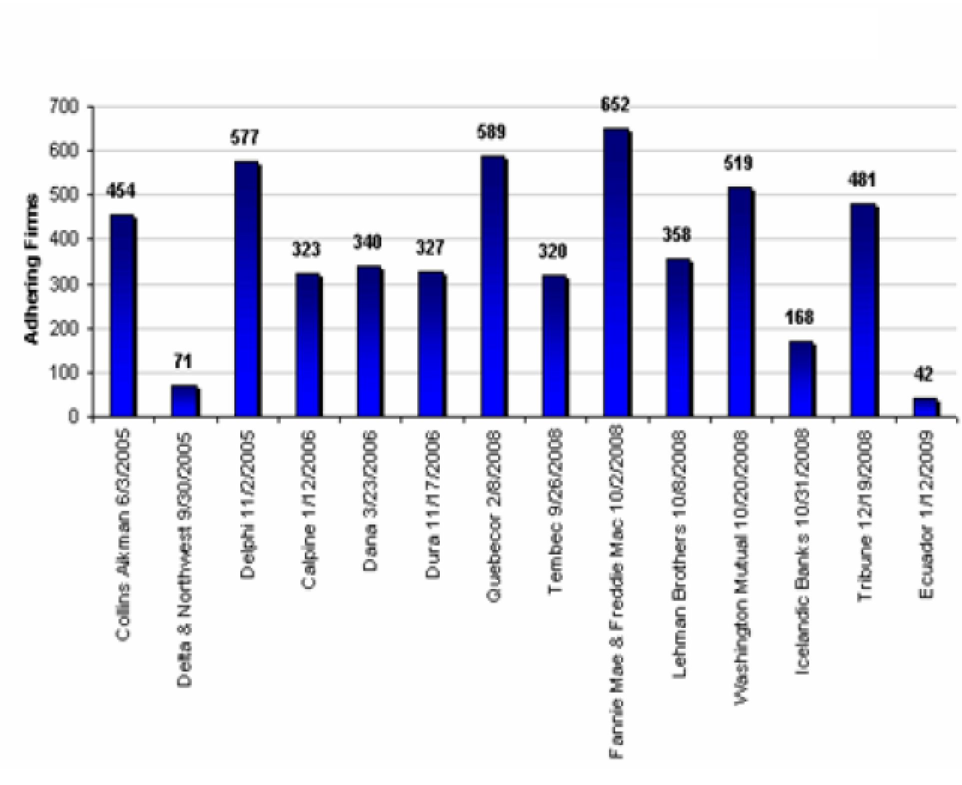
Prior to the Big Bang Protocol, an auction process took place and most market participants signed protocols (a legal document amending all previous trades) to celebrate an auction in order to determine the final recovery rate of a defaulted entity. The process arose because there were concerns that the sheer size of outstanding CDS notional amounts relative to the amount of deliverable bonds would set off a competition between CDS investors to acquire bonds to deliver, artificially increasing the price. Figure 1.17 shows the most important historical auction protocols with the number of adhering firms and the date.

The Big Bang Protocol establishes that the credit event auction methodology will be hardwired into standard CDS contracts on a global basis while leaving only the specific auction settlement terms for each credit event to be determined shortly before to the auction.

Finally, under the current CDS contract, protection against a credit event begins on the business day that follows the trade date. As such, two trades buying and selling CDSs from the same reference entity for the same notional amount but on different days are not truly offsetting. For example, suppose that an investor sold protection today and then entered into an offsetting transaction to close off the exposure a week later (bought protection). With a T+1 effective date for protection, there is a "stub" or window of seven days where the investor is short and does not have the buy protection leg in effect. Under the existing contract, this would persist until the first trade matures. The investor could find out that a credit event occurred during this seven day window. Creating a standard date for the existence of protection regardless of trade date solves this problem. Now, we analyse the main changes en each region.

- **North American changes**

Figure 1.17: Historical auction protocols: Adhering parties & protocol dates



Source: Markit, ISDA

1. Restructuring clauses changes

2. Fixed coupons

As we have mentioned before, prior to the Big Bang Protocol the standard clause in North America was Mod R for investment grade companies, and the XR clause for high yield firms. With the introduction of the Big Bang Protocol, the restructuring event exists as credit event. The reason for this is that many cases of restructuring are included as default in Chapter 11.

Another main change is the introduction of two fixed coupons. The spread will be 100 b.p. for the investment grade companies, and 500 b.p. for high yield companies. Formerly, as the CDS spread changes every day, no contract had the same spread to be paid. This makes netting very complex. With the Big Bang Protocol, the CDS spread is fixed for all contracts; hence, there will be an upfront paid at time zero to make the traders indifferent[1], and to facilitate future netting.

- **European changes**

The Small Bang Protocol introduces the changes in the European market. In Europe, in contrast to the United States regulation, there is no unique regulation that defines the default event. Each country has its own regulation, making the restructuring event not so clear in the different local regulations. Therefore, it is necessary to define which bonds are acceptable for delivery if a restructuring event occurs.

The other difference is the fixed coupon. There will be 25, 100, 500 and 1000 b.p. spread contracts. The reason for this is that traders prefer to enter into contracts that are closer to the previous running spread. However, this fact reduces future netting of the contracts.

- **Asian and Japanese changes**

The Asian and Japanese changes are similar to the North America changes. The fixed coupons will be 25, 100, and 500 basis points. The standard clause for the restructuring event will remain the Full Restructuring clause.

1.5.3 Quantification of the restructuring event in the CDS price

How do the different restructuring clauses affect the CDS market price?

Packer and Zhu (2005), in their article "Contractual terms and CDS pricing", estimate the main differences between the prices of CDS contracts as a function of the restructuring event included in the CDS contracts, for the period from 11 February 2003 to 3 June 2004, using the Markit database. The main results of their study on the CDS quote, changing only the restructuring event for each issuer, are shown in Figure 1.18.

[1] See Beumee et al. (2009) for more details.

Figure 1.18: CDS spread differences

CDS spread differences

	FR–MR	MM–MR	FR–NR	MR–NR
Number of observations	98,833	14,511	34,431	52,232
Mean[1]				
Percentage difference (%)	2.77*	1.33*	7.49*	4.25*
Level (basis points)	3.36*	1.42*	7.65*	4.68*
Median[2]				
Percentage difference (%)	3.06*	1.22*	7.52*	4.33*
Level (basis points)	1.70*	0.65*	4.58*	2.60*
λ^3	1.00	1.35	0.38	–0.30

[1] * shows that the mean is different from zero at a significance level of 95% based on the t-test. [2] * shows that the median is different from zero at a significance level of 95% based on the sign rank test. [3] Defined as the ratio between the percentage change in expected losses-given-default and the percentage change in CDS spreads. Table 2

Note: FR = CR (Full restructuring), NR=XR (No restructuring)

Source: Packer and Zhu (2005)

We have selected the year 2007, as a sample prior to the Big Bang Protocol to estimate the daily median of the ratio for every issuer of each restructuring clause with respect to the full restructuring clause, differentiating the results by regions. For this analysis, we used the 5-year CDS contract because of its liquidity and we must not lose sight of the next equation of the restructuring event quote for the same issuer and currency. By definition, as the restructuring event is wide, we observe the following relation with respect to the restructuring event price for each CDS issuer for the same tenor contract:

CR>=MM>=MR>=XR[2]

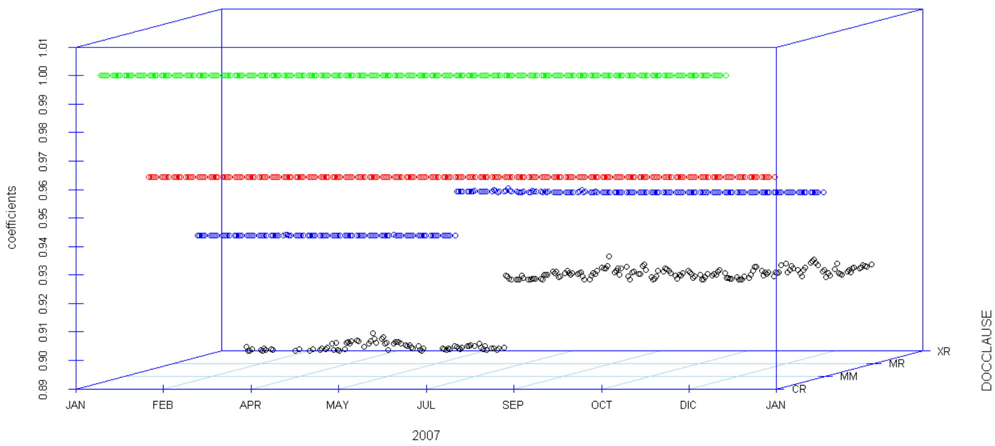
Below we show the results obtained by regions. We start with the case of North America, one of the biggest CDS markets (Figure 1.19). We observe that the daily median ratio is almost constant in the case of the MM ratio, in contrast to the MR and XR that show small jumps in the ratio time series. [3] The observed ratio values are similar to those of to the "Markit.com User Guide", in February 2008 (Markit, 2008), with ratio values of MM 96%, MR 95%, XR 91.5%. In Europe (Figure 1.20), we observe that those ratios present a similar pattern to the North American case, but with less volatility. The Japanese case (Figure 1.21) is special because the restructuring event is regulated in a total different way than the rest of the geographies; thus the XR quote is very different from the other observed values (around 78%). It is also worth mentioning that the MR and MM ratios converge clearly at the end of 2007.

Finally, we observe these ratios in the regions where we have fewer observations. It is interesting to note the instability of those ratios, reflecting a good proxy of the market's illiquidity (Figures 1.22 and 1.23). Therefore, it is easy to observe that in terms of restructuring event, these regions are more volatile than the markets in the developed regions, such as North America, Europe or Japan.

[2] CR: Full restructuring clause, MM: Modified modified restructuring clause, MR: Modified Restructuring and XR: No Restructuring clause. These clauses has been explained above.

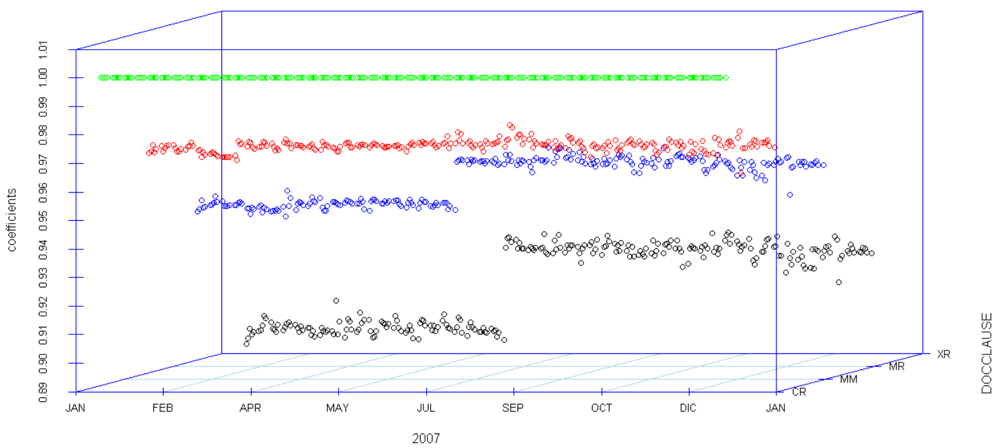
[3] Those jumps were perhaps due to a specific change in the CDS convention, but we could not find the exact reason for them.

Figure 1.19: North American restructuring clause ratio medians. Year 2007



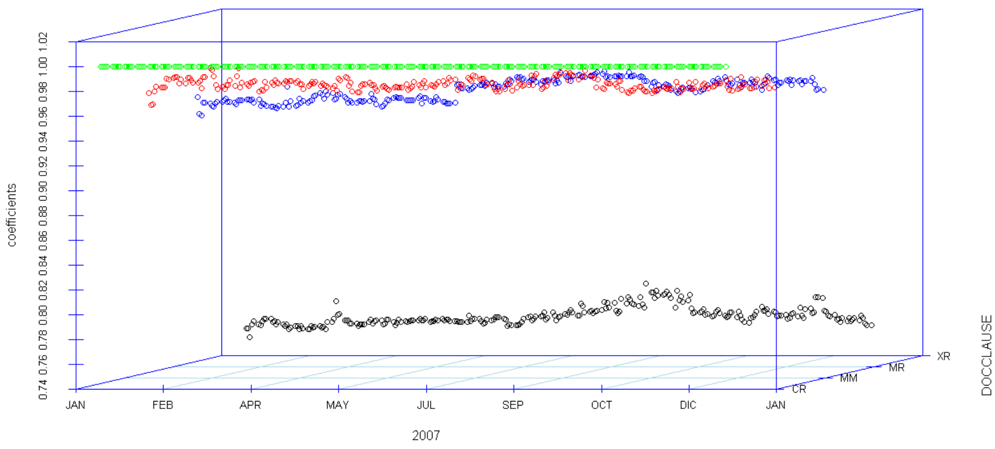
Note: Y-axis: Daily Median Ratio Value.. X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR). The base denominator is CR, for this reason, the CR ratio is always 1.

Figure 1.20: European restructuring clause ratio medians. Year 2007



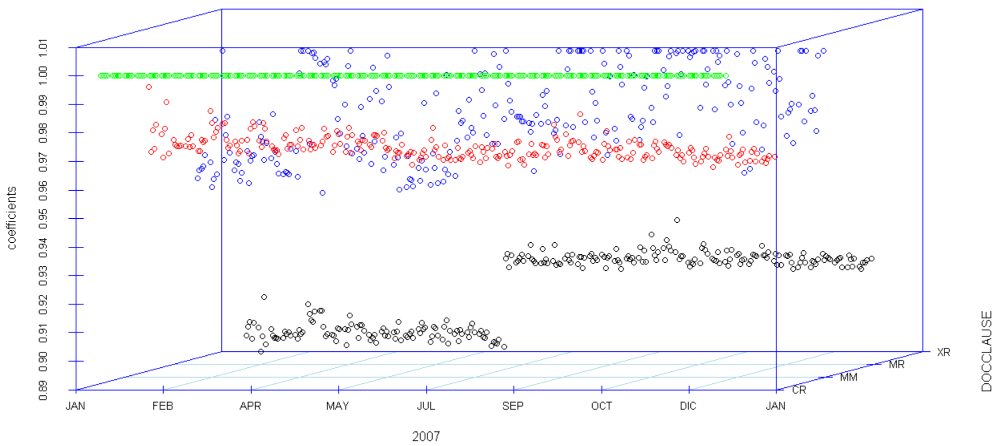
Note: Y-axis: Daily Median Ratio Value.. X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR). The base denominator is CR, for this reason, the CR ratio is always 1.

Figure 1.21: Japanese restructuring clause ratio medians. Year 2007



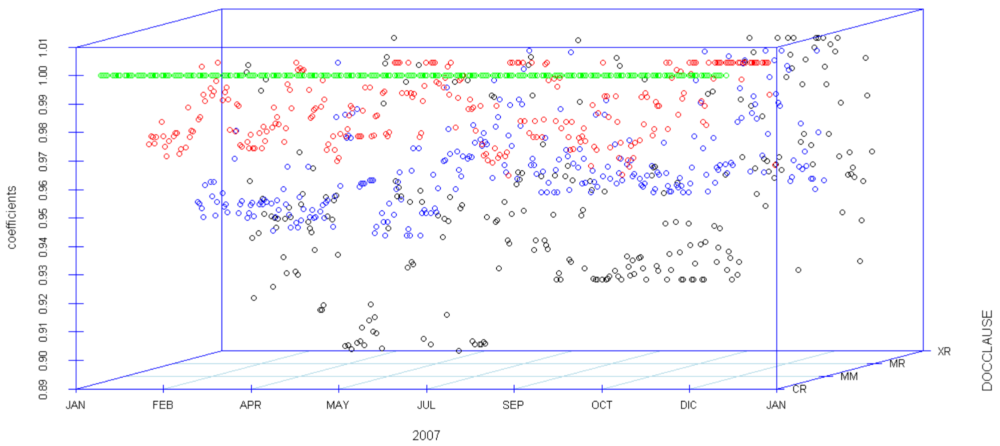
Note: Y-axis: Daily Median Ratio Value.. X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR). The base denominator is CR, for this reason, the CR ratio is always 1.

Figure 1.22: Latin American restructuring clause ratio medians. Year 2007



Note: Y-axis: Daily Median Ratio Value.. X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR). The base denominator is CR, for this reason, the CR ratio is always 1.

Figure 1.23: African restructuring clause ratio medians. Year 2007



Note: Y-axis: Daily Median Ratio Value.. X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR). The base denominator is CR, for this reason, the CR ratio is always 1.

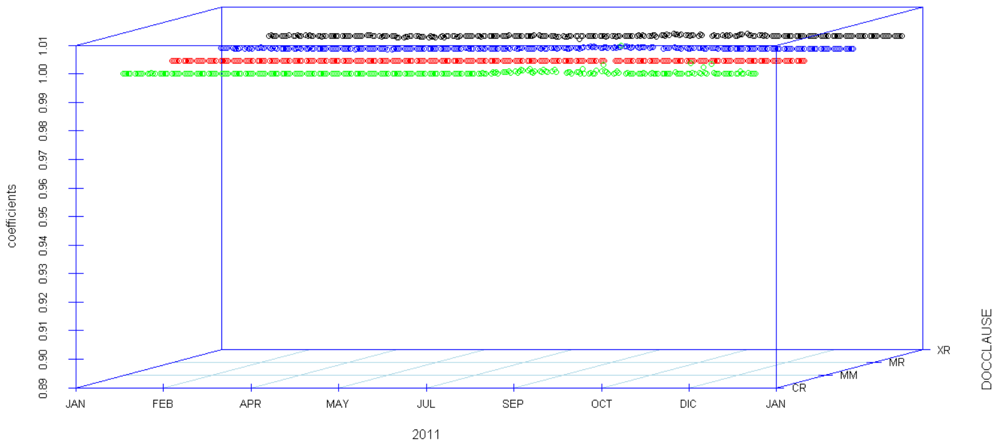
As we mentioned before, after the Big Bang Protocol and with the great standardisation of the CDS contracts, we observe that the MM clause gained more importance in Europe, with more quotes than the CR clause. In North America, we observe the same trend with the XR clause increasing its quotes in contrast to the rest of restructuring clauses. In addition, it is important to highlight that the CDS prices from 2010 onwards are almost the same regardless of their restructuring clause (see Figures 1.24, 1.25, 1.26). This can be motivated by two reasons:

1. By Big Bang Protocol itself, since it establishes a Credit Derivatives Determinations Committee (DC) to determine if credit and succession events occurred. Thus, the new protocol provides more transparency and standardisation to the default event, implying less differentiation in the CDS prices in terms of the restructuring clauses.

2. The CDS prices provided by Markit are composite prices; that is, they are the average prices for an issuer with a determined restructuring clause and currency. These prices go through a series of filters guaranteeing the information quality. However, they are not "real" transaction prices. After consulting with Markit, they informed us that they have to provide different restructuring clause quotes on a daily basis, as financial entities still hold old contracts that need to be revalued. However, after the Big Ban Protocol, liquid markets to estimate the price of the different restructuring clauses for an issuer have disappeared.

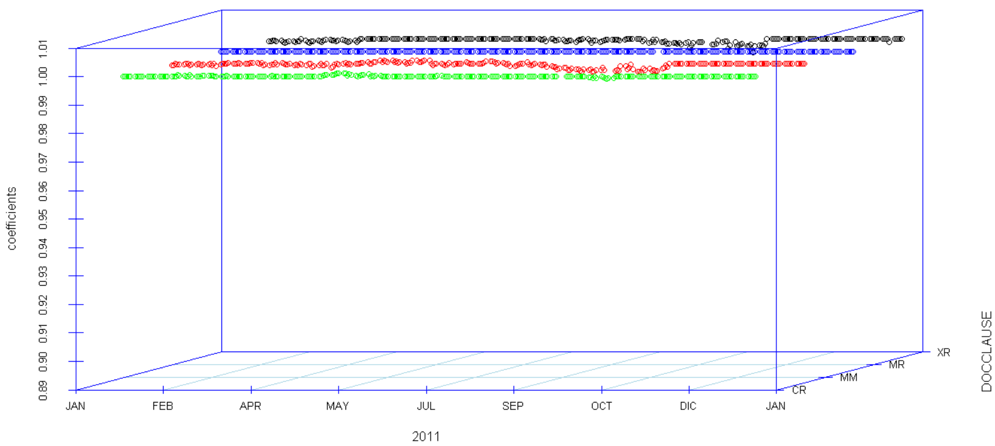
Therefore, we can conclude that the restructuring event was presented in the price of the CDS market prior to the Big Bang Protocol, as there is a theoretical basis. However, after the new protocol, the impact of the restructuring event on the price of the CDS market has been diluted and has lost importance by the increased standardisation of the CDS market.

Figure 1.24: European restructuring clause ratio medians. Year 2011



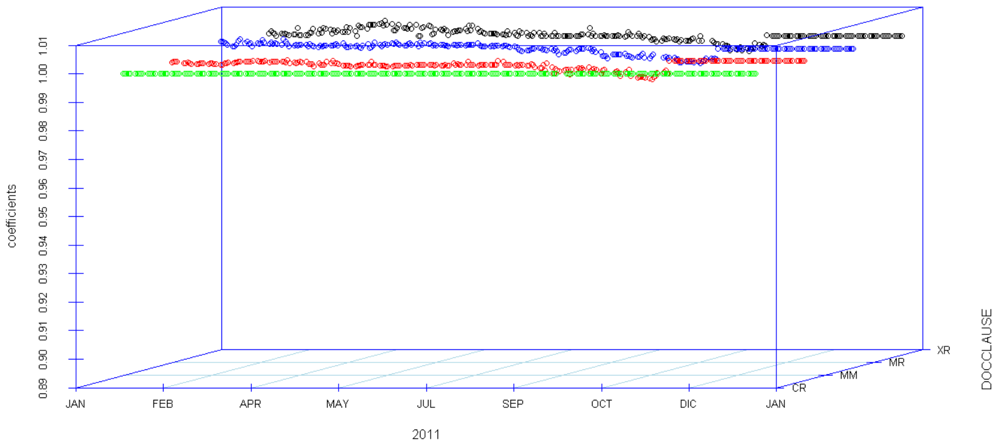
Note: Note: Y-axis: Daily Median Ratio Value. (CR Base denominator). X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR).

Figure 1.25: North American restructuring clause ratio medians. Year 2011



Note: Note: Y-axis: Daily Median Ratio Value. (CR Base denominator). X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR).

Figure 1.26: Asian restructuring clause ratio medians. Year 2011



Note: Note: Y-axis: Daily Median Ratio Value. (CR Base denominator). X-axis: Year 2007. Green Line: Ratio (CR/CR). Red Line: Ratio (MM/CR). Blue Line: Ratio (MR/CR). Black Line: Ratio (XR/CR).

1.6 Outlook for FX adjustment on CDS prices

Is there an adjustment in the CDS quote for an issuer depending on the currency of the contract? Does this adjustment, if any, depend on the type of counterparty?

Reviewing financial literature, we found the article "The influence of FX risk on credit spreads" written by Ehlers and Schonbucher (2006). This article analyses the different prices in the CDS contract for the same issuer and different currency. The majority of those differences are covered by two factors. The first one is the possible correlation between the FX and the default issuer. The second one is an additional jump of the depreciation of the local currency under the issuer default scenario, anticipating a general recession for the local economy. This article shows that the first factor, the correlation between the FX and the issuer default, cannot explain the different quotations in terms of the currency of the CDS contract for the Japanese issuers.

Another interesting article is "Currency dependence of corporate credit spreads", by Jankowitsch and Pichler (2005). The article is based on corporate bonds issued in several currencies for a big sample of firms, and it shows that there is a specific spread quotation for each firm depending on the currency of the issue. Ehlers ans Schonbucher explained in their article that one of the problems of the Jankowitsch study is that the bonds could have different regulations. This problem can be avoided by using the CDS market, as the issuers have the same ISDA regulation.

Our analysis is structured in the following way: First, we select 5-year CDS contracts for all European issuers in different currencies, using only the issuers that have CDS contracts with the most common restructuring clauses (MM in Europe). Thus, we have opted for those issuers in the sample, analysing their own CDS spreads in the following currencies: dollar (USD), Japanese yen (JPY), British pound (GBP), Swiss franc (CHF), and

Australian dollar (AUD) for the European case, and we have used the senior unsecured debt for the type of CDS debt. In Table 1.5, we show the main statistics of these distributions. Row “Abs. b.p.” stands for the distribution for the European issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row “Rel(%)” stands for the distribution for the European issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Table 1.5: FX risk in European issuer CDS prices. USD, JPY and GBP currencies

CURRENCY		*USD*					*JPY*					*GBP*			
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*
1/30/07	Abs. b.p.	537	0.0	0.0	0.0	0.0	302	-2.5	-0.5	-1.9	0.1	347	0.0	0.0	0.0
1/30/07	Rel (%)	537	100.0%	100.0%	100.0%	100.0%	302	90.9%	95.7%	95.4%	100.5%	347	100.0%	100.0%	100.0%
1/30/08	Abs. b.p.	566	0.0	0.0	0.0	0.0	351	0.0	0.2	0.3	0.6	383	0.0	0.0	0.0
1/30/08	Rel (%)	566	100.0%	100.0%	100.0%	100.0%	351	100.0%	100.3%	100.4%	100.7%	383	100.0%	100.0%	100.0%
1/30/09	Abs. b.p.	558	0.0	0.0	0.0	0.0	315	0.0	0.5	2.8	1.4	382	0.0	0.0	0.0
1/30/09	Rel (%)	558	100.0%	100.0%	100.0%	100.0%	315	100.0%	100.4%	100.5%	100.7%	382	100.0%	100.0%	100.0%
1/29/10	Abs. b.p.	534	0.0	0.0	0.0	0.0	314	0.0	0.1	0.4	0.6	371	0.0	0.0	0.0
1/29/10	Rel (%)	534	100.0%	100.0%	100.0%	100.0%	314	100.0%	100.1%	100.3%	100.7%	371	100.0%	100.0%	100.0%
1/31/11	Abs. b.p.	439	-1.6	0.2	-0.7	0.8	179	-0.4	0.3	0.5	1.4	260	-0.1	0.0	0.0
1/31/11	Rel (%)	439	99.1%	100.2%	100.4%	101.2%	179	99.7%	100.4%	101.1%	101.9%	260	99.9%	100.0%	100.1%
1/30/12	Abs. b.p.	458	0.0	0.0	0.0	0.0	215	0.0	0.0	0.0	0.0	285	0.0	0.0	0.0
1/30/12	Rel (%)	458	100.0%	100.0%	100.0%	100.0%	215	100.0%	100.0%	100.0%	100.0%	285	100.0%	100.0%	100.0%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Looking at the first results, we observe that for the European issuers, their CDS contracts in EUR quote very similar to their USD, JPY, GBP CDS contracts, except in January 2011. We have found two reasons for this fact. The first one is the big correlation between the eurozone and the US economy, in an increasingly globalized world. This also happens between Europe and United Kingdom, given the strong economic relationship between them. The second factor is related to the market belief in the independent relationship between a single European company default and its possible systemic spill-over to the rest of the European economy. This means that the market estimates that any European corporate default could collapse the whole European financial system. However, this highlights the fact that, since the 2010 European crisis, the market feeling has changed and begun quoting USD CDS contracts much higher than EUR CDS contracts. Finally, we must not lose track of our MM restructuring event sample criterion. This is the most used clause in Europe for the corporate counterparties; therefore, we are leaving out of the analysed sample the European government CDSs, as they are normally quoted in the CR clause. We will focus on this topic later.

On the other hand, in the JPY CDS quotations for European issuers, we distinguish two stages: The first one, in 2007 and prior to the crisis, we see a small negative premium in the JPY CDS contracts. This means that the market paid less to hedge the European issuer risk in JPY than in EUR. The lack of default risk is a possible reason for this, and perhaps, an additional FX risk in the JPY contracts. The other possibility is the idiosyncrasy of the Japanese credit market itself, where the observed spreads are lower than in the rest of the regions. From 2008 onwards, with the global financial crisis and its increasing intensification, the market quoted a positive adjustment in JPY contracts, meaning that they are more expensive in median than European contracts for European issuers as the eurozone is less correlated with Japan.

To conclude this first analysis, in Table 1.6 we show the results for the European case in two other important currencies, such as CHF and AUD. In the CHF currency, the US and GBP comments above apply to this particular case, due to the big commercial relationship between Switzerland and the eurozone. Finally, the AUD results are very similar to the Japanese case; thus, we could use the same explanation.

In the second analysis, we focus on US issuers. We have chosen those contracts which have MR as the restructuring clause. The selected currencies for this analysis are EUR, JPY and AUD. Table 1.7 presents the main statistics of these distributions. From these results, we see that there is a symmetric effect between the European issuers with the US CDS contracts and US issuers with the EUR CDS contracts. This means that the FX adjustment is practically zero, as we mentioned in the European analysis, except in the year 2011. In the case of a US issuer with a JPY CDS contract, we observe a general negative FX adjustment meaning that the market perceives an additional risk to hedge the currency risk. As we mentioned above, another reason for this can be the lower rate and credit spreads in Japan. There are exceptions where we observe a positive FX adjustment for some issuers, meaning that the buyer of protection is willing to pay a higher premium to hedge the issuer risk in a foreign currency such as the JPY. The case of the AUD (last column) is very similar to the JPY case.

Table 1.6: FX risk in European issuer CDS prices. CHF, and AUD currencies

CURRENCY		*USD*					*JPY*				
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*
1/30/07	Abs. b.p.	203	0.0	0.0	0.0	0.0	263	-2.8	-0.8	-1.9	0.0
1/30/07	Rel (%)	203	100.0%	100.0%	100.0%	100.0%	263	89.3%	94.1%	94.7%	100.3%
1/30/08	Abs. b.p.	270	0.0	0.0	0.0	0.0	312	-0.1	0.1	0.2	0.5
1/30/08	Rel (%)	270	100.0%	100.0%	100.0%	100.0%	312	99.9%	100.2%	100.2%	100.6%
1/30/09	Abs. b.p.	300	0.0	0.0	0.0	0.0	248	0.0	0.6	3.8	1.6
1/30/09	Rel (%)	300	100.0%	100.0%	100.0%	100.0%	248	100.0%	100.4%	100.6%	100.8%
1/29/10	Abs. b.p.	301	0.0	0.0	0.0	0.0	256	0.0	0.1	0.3	0.6
1/29/10	Rel (%)	301	100.0%	100.0%	100.0%	100.0%	256	100.0%	100.1%	100.3%	100.7%
1/31/11	Abs. b.p.	55	-0.5	0.7	0.7	1.6	162	-1.7	-0.1	-0.6	0.4
1/31/11	Rel (%)	55	99.6%	100.8%	101.2%	102.9%	162	98.7%	99.9%	98.7%	100.5%
1/30/12	Abs. b.p.	168	0.0	0.0	0.0	0.0	226	0.0	0.0	0.2	0.0
1/30/12	Rel (%)	168	100.0%	100.0%	100.0%	100.0%	226	100.0%	100.0%	99.8%	100.0%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Table 1.7: FX risk in US issuer CDS prices. EUR, JPY and AUD currencies

CURRENCY		*EUR*					*JPY*					*AUD*				
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*
1/30/07	Abs. b.p.	776	0.0	0.0	0.0	0.0	405	-0.3	0.0	-0.8	0.0	387	-0.5	-0.1	-1.2	0.0
1/30/07	Rel (%)	776	100.0%	100.0%	100.0%	100.0%	405	99.2%	99.8%	99.3%	100.2%	387	98.9%	99.6%	98.9%	100.1%
1/30/08	Abs. b.p.	814	0.0	0.0	0.0	0.0	478	-0.9	0.0	-0.4	0.0	445	-1.1	-0.2	0.5	0.0
1/30/08	Rel (%)	814	100.0%	100.0%	100.0%	100.0%	478	99.4%	99.9%	99.8%	100.1%	445	99.1%	99.8%	99.7%	100.0%
1/30/09	Abs. b.p.	778	0.0	0.0	0.0	0.0	417	-3.2	-0.8	-5.4	0.0	365	-4.9	-1.1	-7.0	0.0
1/30/09	Rel (%)	778	100.0%	100.0%	100.0%	100.0%	417	98.9%	99.5%	99.3%	100.0%	365	98.8%	99.3%	99.2%	100.0%
1/29/10	Abs. b.p.	729	0.0	0.0	0.0	0.0	404	-1.7	-0.7	-1.5	-0.1	384	-2.2	-0.8	4.2	0.2
1/29/10	Rel (%)	729	100.0%	100.0%	100.0%	100.0%	404	98.7%	99.1%	99.3%	99.9%	384	98.6%	99.1%	99.3%	99.8%
1/31/11	Abs. b.p.	599	-1.2	-0.1	1.1	1.2	220	-0.9	0.3	-0.1	1.4	147	-1.7	-0.1	3.8	3.3
1/31/11	Rel (%)	599	98.5%	99.9%	99.3%	100.7%	220	99.3%	100.2%	100.5%	101.5%	147	98.3%	99.9%	99.2%	102.1%
1/30/12	Abs. b.p.	614	0.0	0.0	0.0	0.0	293	-0.1	0.0	-0.6	0.0	242	0.0	0.0	0.5	0.0
1/30/12	Rel (%)	614	100.0%	100.0%	100.0%	100.0%	293	100.0%	100.0%	99.8%	100.0%	242	100.0%	100.0%	99.8%	100.0%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

The following analysis focuses on the Japanese economy (Table 1.8). In this case, we selected the CR clause, as it is the standard, and the currencies USD, EUR and AUD. We notice that for the Japanese issuers with the USD CDS contracts, there is a positive FX adjustment that is in line with the result shown by Ehlers and Schonbucher (2006). However, their estimation was higher than our results, as they only selected the big corporates, and in our analysis, we are estimating the average effect for all the issuers with CDSs in foreign currency. In the case of the euro, we see the same pattern than the US dollar. However, this positive adjustment is higher than before, perhaps reflecting the market belief of a lower correlation between the Japanese economy and the eurozone than Japan and the US economy. Finally, we analyse the AUD CDS contracts, where we see that the number of observations are reduced over time and, at the same time, the positive FX adjustments have increased. As the AUD CDS sample is smaller than the EUR and USD samples, and as a consequence contains the biggest Japanese corporations, which are the ones that have more systemic risk, the main statistics of the main statistics of the FX adjustment are higher.

In the previous analysis, we saw the main statistics for all the issuers by regions; however, by following the philosophy of rating agencies such as Moody's [see Cailleteau et al. (2008)], or S&P, which highlight that the country risk only materialises in those firms where its local rating is higher to the foreign country ceilings, we should look at only the best credit rated firms. For this reason, in the next analysis, we selected AA issuers in Japan, and found the next results (Table 1.9). These last results are very similar to those presented for all of the Japanese issuers, it being quite reasonable to think that the positive FX adjustment in the quotation in this case would be higher than in the first case. Therefore, there is a positive FX adjustment in the corporate CDS prices that has increased with the crisis, but such an adjustment, in terms of the median or mean, is small for the corporate issuers. This means that the FX adjustment in CDS price for the corporate counterparties only exists for the bigger ones, where there is a strong correlation between the issuer default and the systemic risk of the local economy.

Table 1.8: FX risk in Japanese issuer CDS prices. USD, EUR, and AUD currencies

CURRENCY		*USD*					*EUR*					*AUD*				
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*
1/30/07	Abs. p.b	213	-0.1	0.0	0.2	0.3	106	0.0	0.2	0.4	0.5	20	0.0	0.1	0.1	0.3
1/30/07	Rel (%)	213	99.7%	100.0%	101.1%	102.9%	106	100.0%	102.1%	102.4%	104.4%	20	100.0%	100.5%	100.6%	101.2%
1/30/08	Abs. p.b	242	-0.2	0.0	0.2	0.3	113	-0.1	0.2	0.8	1.4	27	0.0	0.3	0.8	1.2
1/30/08	Rel (%)	242	99.2%	100.0%	100.3%	100.7%	113	99.7%	100.4%	101.5%	103.1%	27	100.0%	100.3%	101.1%	101.6%
1/30/09	Abs. p.b	259	-0.3	0.0	0.1	0.7	116	-0.5	0.1	0.5	2.0	12	-0.8	0.6	3.2	2.6
1/30/09	Rel (%)	259	99.8%	100.0%	100.0%	100.4%	116	99.8%	100.1%	100.3%	101.2%	12	99.8%	100.1%	100.3%	100.6%
1/29/10	Abs. p.b	241	-0.2	0.0	0.1	0.1	107	-0.3	0.0	0.5	0.7	12	-0.4	0.0	-4.1	0.6
1/29/10	Rel (%)	241	99.8%	100.0%	100.3%	100.0%	107	99.7%	100.0%	100.6%	100.7%	12	99.6%	100.1%	100.0%	100.2%
1/31/11	Abs. p.b	159	-0.7	0.0	0.9	0.9	65	-1.0	0.1	3.7	3.0	4	2.4	8.4	14.8	20.8
1/31/11	Rel (%)	159	99.3%	100.0%	100.7%	101.3%	65	98.2%	100.1%	100.8%	101.4%	4	102.8%	106.3%	104.1%	107.6%
1/30/12	Abs. p.b	161	0.0	0.0	2.9	2.2	74	0.0	2.0	5.8	5.7	3	0.0	0.0	10.5	15.8
1/30/12	Rel (%)	161	100.0%	100.0%	102.5%	101.4%	74	100.0%	101.4%	104.9%	104.9%	3	100.0%	100.0%	109.2%	113.8%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Table 1.9: FX risk in AA Japanese issuer CDS prices. USD, and EUR currencies

CURRENCY		*USD*						*EUR*					
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Max*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Max*
1/30/07	Abs. p.b	38	0.0	0.0	0.1	0.3	0.9	26	0.0	0.2	0.1	0.4	0.9
1/30/07	Rel (%)	38	99.7%	100.5%	102.6%	106.1%	122.5%	26	99.7%	104.0%	103.3%	106.4%	122.5%
1/30/08	Abs. p.b	35	-0.2	0.0	0.4	0.8	4.8	24	-0.2	0.3	0.7	1.8	4.8
1/30/08	Rel (%)	35	98.9%	100.0%	101.6%	104.1%	117.3%	24	99.1%	101.7%	102.8%	104.8%	117.3%
1/30/09	Abs. p.b	45	-0.1	0.0	0.3	1.1	15.3	26	-1.0	0.3	-0.1	2.1	7.5
1/30/09	Rel (%)	45	99.8%	100.0%	100.5%	101.8%	115.8%	26	98.6%	100.3%	100.2%	102.2%	110.0%
1/29/10	Abs. p.b	41	0.0	0.0	0.0	0.0	5.8	23	-0.3	0.0	0.4	0.3	5.8
1/29/10	Rel (%)	41	99.9%	100.0%	101.0%	100.0%	123.6%	23	99.4%	100.0%	101.4%	100.4%	123.6%
1/31/11	Abs. p.b	33	-0.9	0.2	1.2	1.1	24.7	18	-1.3	-0.8	1.2	0.1	24.3
1/31/11	Rel (%)	33	98.4%	100.3%	101.8%	103.8%	141.3%	18	95.9%	98.1%	100.7%	100.1%	140.7%
1/30/12	Abs. p.b	27	0.0	0.0	3.1	1.3	63.4	15	0.0	1.2	5.5	2.6	63.4
1/30/12	Rel (%)	27	100.0%	100.0%	104.4%	101.7%	188.8%	15	100.0%	101.5%	108.0%	105.4%	188.8%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Table 1.10: FX risk in European government issuer CDS prices. USD, and JPY currencies

CURRENCY		*USD*						*JPY*					
Date		*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Max*	*Nº Obs*	*1Q*	*Median*	*Mean*	*3Q*	*Max*
1/30/07	Abs. p.b	26	0.0	0.0	0.0	0.0	0.0	9	-0.3	-0.1	-0.5	0.0	0.1
1/30/07	Rel (%)	26	100.0%	100.0%	100.0%	100.0%	100.0%	9	96.2%	96.5%	95.9%	100.0%	108.6%
1/30/08	Abs. p.b	30	0.0	0.0	0.0	0.0	0.0	9	-1.5	-0.4	-0.7	-0.1	0.1
1/30/08	Rel (%)	30	100.0%	100.0%	100.0%	100.0%	100.0%	9	96.3%	98.1%	98.0%	99.2%	100.3%
1/30/09	Abs. p.b	29	0.0	0.0	0.0	0.0	0.0	7	-0.7	-0.1	-0.5	0.0	1.3
1/30/09	Rel (%)	29	100.0%	100.0%	100.0%	100.0%	100.0%	7	99.3%	99.9%	99.4%	100.0%	100.5%
1/29/10	Abs. p.b	29	0.0	0.0	0.0	0.0	0.0	11	-0.3	-0.1	0.2	0.0	6.7
1/29/10	Rel (%)	29	100.0%	100.0%	100.0%	100.0%	100.0%	11	99.7%	99.9%	99.3%	100.0%	101.0%
1/31/11	Abs. p.b	23	1.4	9.4	24.8	46.4	89.1	2	53.4	58.9	58.9	64.4	69.9
1/31/11	Rel (%)	23	102.7%	123.0%	119.5%	132.8%	141.2%	2	116.1%	123.6%	123.6%	131.1%	138.6%
1/30/12	Abs. p.b	25	0.0	5.8	26.7	61.0	111.1	5	61.0	70.9	69.0	80.3	94.1
1/30/12	Rel (%)	25	100.0%	107.2%	117.6%	124.2%	174.6%	5	133.2%	153.3%	150.7%	169.1%	174.7%

Note: Row "Abs. b.p." stands for the distribution for the specific region issuers of the difference between the CDS spread in foreign currency and the CDS spread in local currency for each issuer in basis points. Row "Rel(%)" stands for the distribution for the specific region issuers of the ratio between the CDS spread in foreign currency over the CDS spread in local currency for each issuer.

Finally, in the last analysis, we focus on the government sector in Europe (Table 1.10) . On this occasion, we use the CR clause, and again the 5-year CDS contract. These are, without doubt, the most interesting results. First, as in the previous cases, we see that the USD contract quotations are the same as the EUR contracts. In the JPY case, the FX adjustment is even negative. However from 2010, the strong correlation between the European government defaults and the possible deep euro depreciation led to an extra premium in foreign currency CDS contracts for European governments.

To sum up, we can conclude this section affirming that there is a substantial FX adjustment in the CDS price when the market estimates a significant adverse impact between the issuer default and the systemic risk of the local economy, as Ehlers and Schonbucher (2006) and Jankowitsch and Pichler (2005) pointed out. However, this FX adjustment is almost negligible for the remaining cases.

1.7 Outlook for recovery in CDS prices

Are the standard recoveries different depending on the type of CDS issuer? How does recovery affect CDS prices? Why do we use different recoveries depending on the region and type of counterparty?

The standard recovery of the market is a fixed value that depends on the region and the underlying asset. Generally, this standard is 40%, with a few exceptions like Japan, where the recovery value is 35%. In other regions, as Africa, Latin America, Eastern Europe or the Middle East, the assumed recovery is 25%. Finally, the recovery value for bank subordinated debt is 20%. The question is, why do we use different recovery standards depending on the region?

The 40% value assumed by the market for the CDS recovery for the unsecured debt is very close to the historic average recovery for unsecured bonds [see Altman et al. (2004)] and shown in the different agencies' rating studies. Moody's report, "Annual default study: Corporate default and recovery rates, 1920-2012", Ou et al. (2013), estimates that the recovery for the unsecured bonds for the period 1982-2012 was 37%, weighting by issuer, or 38%, weighting by volume. In 2012, the recovery was 43.4% by issuer and 40.2% by volume.

Japan's current insolvency regime is a complicated system consisting of five separate legal proceedings [see Tan et al. (2004)]. The formal legal proceedings are often bypassed; informal negotiations among the parties, known as "private arrangements" (shiteki-seiri), are more common than formal proceedings because Japan's insolvency regime and business practices are deeply influenced by its corporate governance system based on cross-shareholdings and long-term relationships among a group of firms, or keiretsu. At the centre of the keiretsu there is frequently a main bank, which is the largest creditor of the group of companies, and often holds shares. In addition to this, the Japanese government plays a much more visible role in the bankruptcy regime than in the rest of the economy. For example, the Japanese government has been involved in specific corporate insolvency cases. For these reasons, the government and banks often support a borrower until the last minute. In Japan the typical court-ruled recovery rate is usually lower than in the US or Europe. By the time the borrower's condition has deteriorated to a point beyond rescue, the value of its assets may have already been greatly diminished and often offers little recovery for creditors. Thus, the market standard for recovery of the Japanese CDS is 35% instead of the 40% in the rest of developed regions.

For the rest of the regions, usually emerging regions, the standard of the market is 25%. However, it is highlighted in Moody's report, "Latin American corporate default and recovery rates update, 1990 to July 2012", Sorensen et al. (2012), that the recovery value for Latin America for unsecured bonds is 35%, similar to the global recovery, 38%. Such discrepancy between the market standard and the historic recovery value could be explained due to the fact that Moody's register started in 1990, and consequently ignores the previous defaults, and some political crises in the eighties, such as the Argentinian crisis, where the recovery value was lower.

How does recovery affect the CDS prices? Duffie (1999) shows that the effect of varying the hazard rate and the recovery rate is offset when the CDS is close to the bond spread for an issuer. Such a mechanism works really well for short-dated bonds and when the bonds are close to par value. Andritzky and Singh (2006) show that the empirical evidence point out that CDS spreads are higher than bond spreads for an issuer in a stress scenario, and this is because it exceeds the traditional basis risk. They mention two different arguments for this. The first one is that the CDS provides over protection assuring the nominal value, given that the bond is far below par value, which leads to the existence of a positive basis, among the CDS and bond spread. The second one is that the buyer of protection will deliver the cheapest-to-deliver bond, therefore the higher the difference between the cheapest-to-deliver bond and the rest of the bonds for that issuer, the higher the basis. Thus, the CDS market accepts constant recovery, while the bond market will be deep below par value in a stress scenario. Therefore, assuming risk neutral probability and consistency between bonds price and CDS prices, a new decrease in the bond price will lead to a large exponential increase in the CDS spread to maintain that relationship. Such an increase will be higher as longer dated bonds and higher bond spreads [see Andritzky and Singh (2007), Singh and Andritzky (2005) and Singh and Spackman (2009)]. Finally, Bilal and Singh (2012) show the importance of estimating the default probability inferred from the CDS market using the CDS spread, and the proxy recovery estimated by the cheapest-to-deliver bond for the Portuguese, Greek, Italian or Spanish crises. Using a constant recovery instead of a stochastic recovery leads to the risk neutral probability inferred from the market to double its value, for instance from 7% to 14% in the recent Portuguese crisis.

To sum up, in this section we have seen the reason why the market uses different standard recoveries depending on the region. Normally, these standard recoveries do not influence in the CDS prices under normal conditions, as Duffie (1999) pointed out. However, it is very important to take into account the stochastic recovery in those cases where the bond price is far below par value.

1.8 Outlook for dataset quality rating

Given the recent credit and illiquidity crisis and the lack of transparency in the credit markets, the question that arises is, could we use all the Markit dataset without applying any filter to estimate the credit sector curves?

Markit provides a data quality rating for the CDS prices [see Markit (2008), Markit (2011) and Mayordomo et al. (2014)]. This means that Markit assigns a daily rating for the published CDS data. The range of this quality rating can be AAA, AA, A, BBB, BB, B, CCC or NR. The ratings are assigned based on qualitative and quantitative criteria. The most important quantitative variable is the number of different clean contributions. The qualitative criteria measures how competitive, liquid and transparent the market is, and whether the trades are time stamped and tradable quotes updated frequently or not. According to Markit, a great deal of confidence can be placed in ratings of BBB or higher, for which a very minimum of three clean contributions are required in addition to the highest scores on qualitative criteria. Markit assigns a AAA rating only for data that has obtained the highest score on the qualitative tests and is based on more than twelve clean contributions.

In this section we propose a very simple regression using our dataset for a particular day to analyse the influence of quality rating over our estimations and our residuals. In the next chapter we will focus on an extensive estimation analysis of the sector credit curves.

Our basic proposed model is

$$p_l = \beta_0 + \beta_1 R_{l,z} + \beta_2 S_{l,i} + \beta_3 G_{l,j} + \mu_l, \ l = 1,2,....L \tag{1.1}$$

where p_l represents the risk premium of the issuer l, and the variables R, S and G are dicotomic variables, representing the different levels of rating, sector, and geographical regions present in the sample. There are n variables R_z, m variables S_i, and k variables G_j, being n, m, and k the number of rating class, sectors, and geographical regions included in the sample. These variables are defined as

$R_{l,z} = 1$ if the CDS denoted by the subindex l has rating z, and $R_{l,z} = 0$ otherwise, for all $z = 1,2,...n$. In total, there are nine rating classes: AAA, AA, A, BBB, BB, B, CCC, D and NR (without rating).

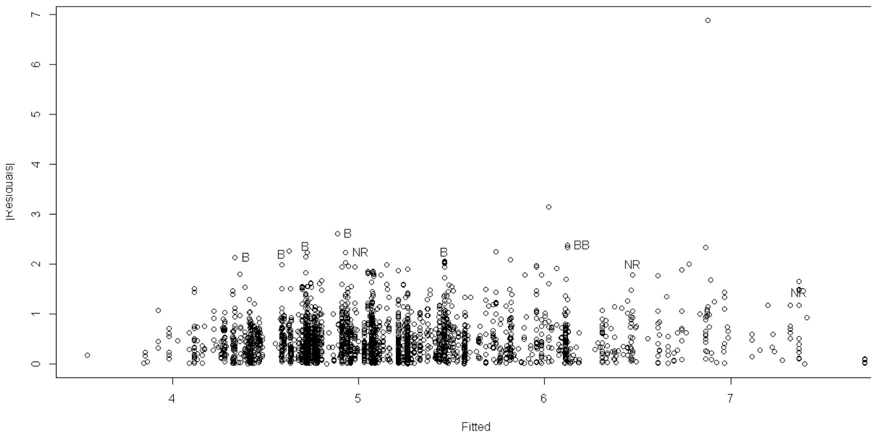
$S_{l,i} = 1$ if the CDS denoted by the subindex l corresponds to a firm that belongs to sector i, and $S_{l,i} = 0$ otherwise, for all $i = 1,2,...m$ .11 sectors are represented in the sample: Basic materials, consumer goods, consumer services, energy, financials, government, health care, industrials, technology, telecommunication services and utilities.

$G_{l,j} = 1$ if the CDS denoted by the subindex l corresponds to a company located in the geographical region j, and $G_{l,j} = 0$ otherwise, for all $j = 1,2,...k$. We have thirteen different regions in the sample: Africa, Asia, Caribbean, E.Eur, Europe, India, Lat.Amer, Middle East, N.Amer, Oceania, Offshore, Pacific and Supra.

In this case, we use the senior debt, as it is the most representative in the CDS market. We focus on a particular date (31 January 2012) to analyse the proposed models' residuals and study if there is any relationship between the data residual size and the data quality rating.

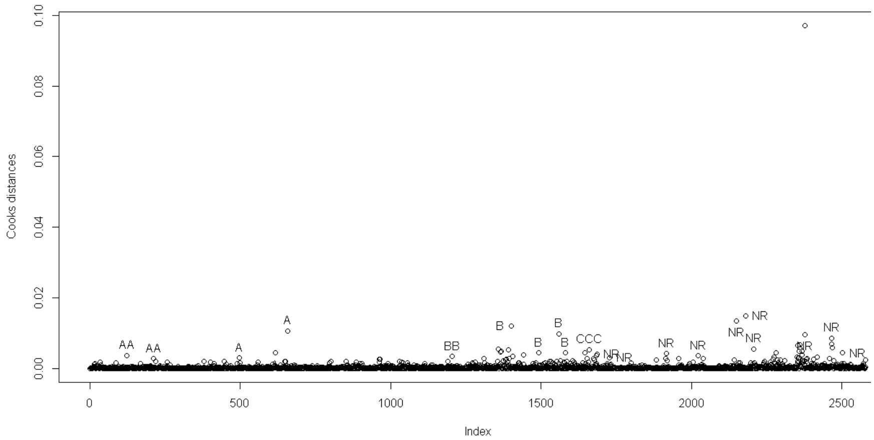
In Figure 1.27, we represent the absolute value of the residuals against the fitted value by the model. It is very easy to note that the biggest residuals are found among the lower quality data. Finally, we present Cook's distance in Figure 1.28. Once again, it should be emphasised that the most influential observations are those that have lowest data quality. By conducting this simple study, we can conclude that it is necessary to apply

Figure 1.27: Markit quality rating for the biggest absolute residual values on 31 January 2012



Note: Y- axis: Residual absolute value for the lineal estimation of the senior 5-year CDS for each issuer as a function of the rating, sector and region (without applying any quality data filter). X-axis: Issuers. Thus, we show the quality ratings for the biggest residuals, which are normally the worst quality ratings.

Figure 1.28: Markit quality rating in terms of Cook's distance on 31 January 2012



Note: Y- axis: Cook's distance for the lineal estimation of the senior 5-year CDS for each issuer as a function of the rating, sector and region (without applying any quality data filter). X-axis: Issuers. Thus, we show the quality ratings for the biggest Cook's distance, which are normally the worst quality ratings.

filters to the database in order to avoid biasing the estimation of the sector credit curves. We will focus on this matter later.

1.9 Conclusion and open questions

In this first chapter, we have reviewed the main aspects of the microstructure of the CDS market. Our main outcomes are the following:

The CDS market is concentrated in North America, Europe and Asia, most of the issuers being A or BBB ratings, and the most representative sectors are financial, industrial and consumer services. The CDS curve slope of an issuer is typically positive, the higher the tenor, the wider the spread, except in a stress scenario. It can also be observed that the usual right-skewed distribution of the CDS spreads grouped by rating sector sometimes lead to the presented "inversion problem" in Subsection 1.4.

What type of restructuring clause should we use to aggregate the different data? As we have seen, prior to the Big Bang Protocol, Markit (2009d), there was higher liquidity in non-standard clauses of CDS contracts, but today the market has changed radically, it being unfeasible to estimate the value of the non-standard clause by regions. Furthermore, we observe that after the Big Ban Protocol there is a higher standardisation of the CDS market reducing the impact of the restructuring event in CDS prices. Therefore, we have opted to use the standard market clause for each issuer depending on its geographical region and counterparty type. We thus propose being consistent with the default definition of each legislation, but we will be inconsistent with a universal definition of default.

Related to the previous point the next question is which currency for each issuer we should use to estimate credit curves. As we have shown, there is a substantial FX adjustment in the CDS price when the market estimates a considerable adverse impact between the issuer default and the systemic risk of the local economy as Ehlers and Schonbucher (2006) and Jankowitsch and Pichler (2005) pointed out. However, this FX adjustment is nearly 0 for the rest of the cases. These conclusions should also be important for pricing loans on matters related to trade finance where country risk exists. Thus, we propose using the standard currency for each issuer, according to its region and counterparty type. We would like to highlight that the standard currency for European governments will be the dollar instead of the euro, given the correlation between the issuer default and the depreciation of the currency.

Regarding the recovery of the CDS, we have seen that the different recovery standards by regions do not influence CDS prices under normal conditions as Duffie (1999) mentioned. However, we have to note that it is very important to take into consideration the stochastic recovery in those cases where the bond price is far below par value. Thus, how can we manage the different standard recoveries of the market? Given that our main objective is to estimate the premium risk of an issuer without an active credit spread, we could assume that these premiums are close to par value. Consequently, the hypothesis on the recovery is not as relevant as we have shown above. In addition to this, we have seen that the standard recovery assumed by the market is in line with the historical recoveries by regions, with only few exceptions such as Latin America. Therefore, we use the standard recovery for each issuer without the need to adjust a common recovery for all the issuers, which would lead to adjusting the market CDS spread.

With regard to the matter of contract maturity, we will use the 5-year CDS spread in later analyses, due to its liquidity, as we pointed out before. Because of the liquidity factor, we also opt to use the senior debt CDS.

Finally, what type of filter should we apply to the dataset? We are quite concerned about this topic, and therefore we propose using three different filters in order to estimate our credit curves and analyse the implications of these filters. The first one will be the use of "non-filters", the second one will be based on the Markit quality rating, and the third one will be based on a fixed sample of the most liquid CDS contracts. We will analyse this matter in-depth in the following chapter.

In conclusion, in this first chapter we have defined criteria to aggregate the dataset in order to estimate the credit curves by rating, sector and region as Basel requires. The different econometrics models to estimate these credit curves will also be analysed in the following chapter.

Chapter 2

Econometric models of credit spreads

2.1 Motivation

Is it a good business for a financial entity to issue a loan with a 5-year tenor, the borrower having a BBB rating, belonging to the utilities sector, located in Europe and paying 300 basis points (b.p.) plus the risk-free rate? What about the same business deal but with a borrower located in Asia?

Any type of investment requires the acquisition of assets (financial, real or both), it being crucial to analyse several features. The three main attributes of financial assets are return, risk and liquidity. The first two are normally taken into consideration when deciding whether to invest in an asset or not. However, liquidity is nowadays more important since the last crisis. Therefore, the investors must analyse the risk and return of those financial assets before taking the investment decision [see among others, Altman (1996), Cebenoyan and Strahan (2001), James (1996) and Guill (2008)]. Consequently, this analysis is carried out by the return on risk-adjusted capital (RORAC).

The main RORAC applications (for a financial entity) in managing credit risk are the following:

1. Criteria for the selection of the investment project. The approval policy establishes criteria for a bank to accept the financial assets or not. When a financial entity uses RORAC, the “new” asset has to be above the minimum value demanded by the entity, for example, the minimum threshold required by stockholders.

2. Risk-based pricing, RBP. It is closely related to the previous point. It establishes the credit margin that a financial entity must receive from the borrowers according to the trend in international credit markets.

3. Risk-adjusted performance, RAP. It consists of monitoring the RORAC of an asset as long as it is in the portfolio of an entity. Thus, the entity could compare the current RORAC with the initial one. If there is a substantial divergence between them, the entity will take action to solve this situation by, for instance,

increasing the cross-selling of products that do not imply any additional risk.

The main limitations of RORAC methodology in the financial literature are as follows:

- The lack of consideration of possible cash flows weighted by the probabilities of occurrence during the life of the loan, given that the majority of loan contracts set up several embedded options. The RORAC does not normally take these options into consideration. The RORAC methodology typically uses initial values or expected values for the entire life of the loan.

- The RORAC uses historical risk parameters. Most of these RORAC analyses ignore the current level of credit spreads and emphasize agency ratings. Therefore, for a fair valuation, we need to calibrate our models to the current market credit spread. Loan proposals which implied an arbitrage between agency rating and the market-implied rating were very common during the last crisis.

Therefore, the determination of borrowers' credit spreads is decisive for any financial entity for several reasons:

- The assignment of prices for new loans or financial guarantees and for the valuation of the banking book.

- Due to the monitoring of the loan portfolio, using market-implied ratings instead of agency ratings.

- CVA quantification of the trading book.

On the latter point, the Basel Committee (2011) in its document "Basel III: A global regulatory framework for more resilient banks and banking systems", sets CVA methodology for the trading book, when the determination of the credit spread for those entities interested in advanced models in their risk management is vital. In a later document, the Basel Committee (2012b) reaffirms the idea of requiring the financial entities to estimate the credit spread curves considering the different factors of rating, sector and region of each counterparty.

It is usually assumed that in the firms that have a CDS contract, this is the key factor that establishes the credit premium risk for a new financial asset [see Longstaff et al. (2003) and Longstaff et al. (2005)]. Thus, a CDS is a key element for any investor when exploiting relative value opportunities across a firm's capital structure (Figure 2.1). All of this being true, there are many unanswered questions: How could we estimate the credit spread for an issuer without CDS? Could we use the Markit dataset, the main source of the CDS prices? Do we need to set up quality filters at different levels of the sample in the Markit dataset? The graphic idea (shown in Figure 2.2) is to build up credit spread curves for every combination of rating, sector and region; thus, we get a proxy for the risk premium of each financial asset without a CDS [see among others, Fabozzi et al. (2007) and Chourdakis et al. (2013)].

On the other hand, given the high volatility period in the credit market in recent years, triggered by the default of Lehman Brothers on 15 September 2008, we observe the presence of big outliers in the distribution of credit spreads in the different groups of rating, industry and region. In the current context of the financial and economic crisis, is the OLS regression the optimal method to estimate credit spread curves? Or is it more efficient to use more robust estimators which are not so affected by the presence of outliers? For a financial institution, it is clear that the best approach is the one that reflects the market trend and minimizes the fluctu-

Figure 2.1: CDS as a key element for other credit markets

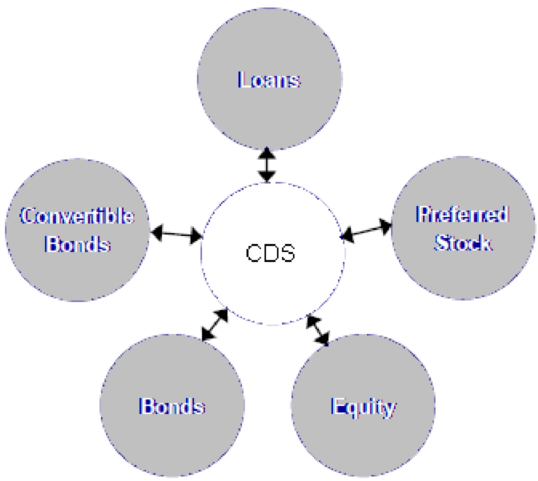
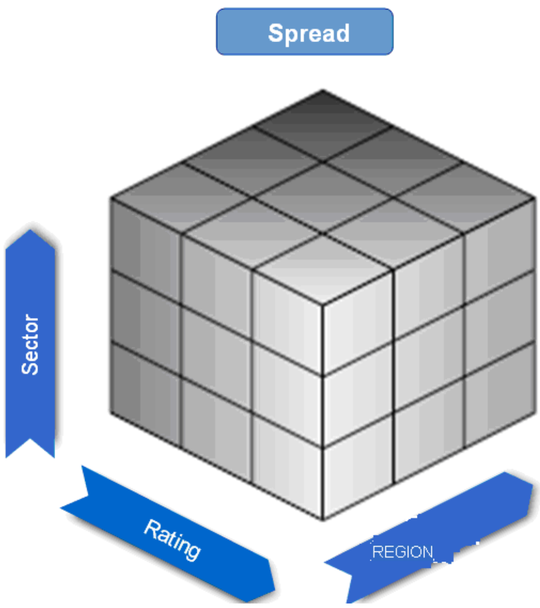


Figure 2.2: Spread curves by rating, sector and region



ations of the estimates.

In addition, we do not have a big enough subsample for each group by rating, industry and region. For this reason, we have to aggregate the information using different criteria. If we use hierarchical models, which prioritize the information of the variables, we use the rating information as the first risk factor, but as a second factor: Should we use the industry or the region of the issuer? And, are there significant differences using alternative hypothesis?

This work contributes to the financial literature in specific ways, since we use a great variety of statistical models to estimate the credit spread curve, also taking into account the special features of the CDS market. In order to conduct the analysis and evaluate the different possibilities that we could use, we compare all the introduced models in this chapter for 2006-2012. We use this time frame as we believe that it is the most relevant period of time for the credit market. We think that this is an adequate starting point to establish a standard methodology in building up credit spread curves for the financial system. Methodology standardization leads to more transparency and rigour in the financial community.

This chapter is divided into five sections in addition to this one. In Section 2.2 we review briefly the two categories of the credit models, structural models and reduced-form models. Then we follow with a description of the econometric models of credit spreads in Section 2.3. In that section, we focus on non-hierarchical regression, differentiating between ordinary least-squares regression and quantile regression. Furthermore, the section also deals with the hierarchical regression. In Section 2.4 we start to analyse the implications of the different presented econometric models with a transversal data analysis. In Section 2.5 we test in depth the different econometric model for the period 2006-2012. At the end of the chapter, we review our main findings and open questions in Section 2.6.

2.2 Introduction: Structural models vs reduced-form models

As we have just pointed out, credit spread modelling is absolutely essential. Classifying credit spread model into two categories is widespread in the financial literature:

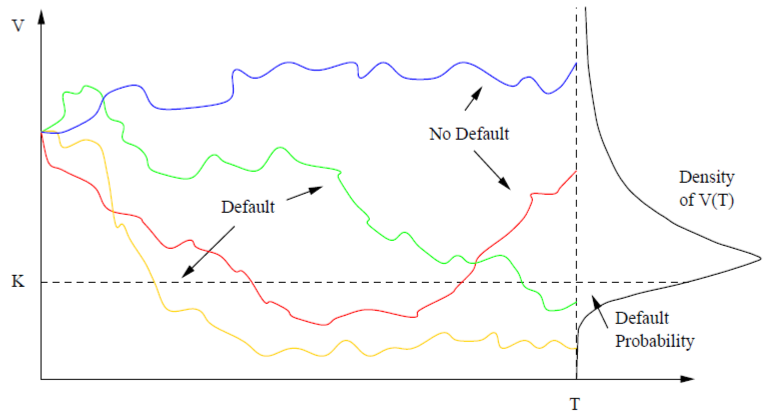
1. Structural models (Merton approach)

2. reduced-form models (intensity approach)

Structural models

Structural models were originally developed by Merton (1974), the so-called "Merton Model" being the cornerstone of such an approach. It is based on the asset value and the capital structure of a company, trying to determine its probability of default. As equity and debt are considered as company value options, we are able to transform them into credit spreads [see Crouhy et al. (2000) and Gordy (2000)].

Figure 2.3: Default in the Merton approach



The main drawback lies in the lack of relevant information for these models, since it is not usually public, such as for asset value or threshold debt. To date, research in this field has shown that this structural approach does not generally properly match the credit market spread and the dynamic of the credit spread, specially in the short run. This approach represents credit models with very strong economic foundations, but they are very limited for pricing debt. In Figure 2.3, we depicted the main idea of the Merton Model in a simple way.

Reduced-form models

The second type of models are the reduced-form (or intensity) models. These models are distinguished by the fact that they do not consider the relation between default and the firm value in an explicit manner. The dynamic of the default is taken as exogenous and is defined by the default intensity. The principal advantage of this approach is that we could calculate the price of the credit financial assets as a risk-free assets, adding the credit spread rate to the risk-free rate. Therefore, instead of asking why the defaults occur, we infer the probability of default from market prices. These models are mainly used for pricing; however, this approach is more difficult to apply in a different context, such as economic capital estimations, due to the lack of link between the probability of default and the asset value. Given that our main goal is to establish criteria for pricing debt of different issuers without CDS, we decided to work with the reduced-form models as they are designed for pricing.

The credit intensity default models are based on one of the more commonly used statistical functions, the "hazard rate" function [see Duffie and Singleton (1999)]. T is a random variable called the time-until-default, or simply survival time, for an asset, to denote this length of time. Let denote $F(t)$ the distribution of T.

$$F(t) = Pr(T \leq t),\ t \geq 0 \tag{2.1}$$

and set

$$S(t) = 1 - F(t) = Pr(T > t),\ t \geq 0 \tag{2.2}$$

where the function $S(t)$ is the survival function. Thus, the following equation stands for the instantaneous probability of default of an asset, which has survived x years.

$$\begin{aligned} Pr[x < T \leq x + \triangle x \mid T > x] &= \tfrac{F(x+\triangle x) - F(x)}{1-F(x)} \\ &\approx \tfrac{f(x)\triangle x}{1-F(x)} \end{aligned} \tag{2.3}$$

The function

$$\frac{f(x)}{1-F(x)} \tag{2.4}$$

represents the value of the density function of the conditional probability of T at the exact time x, given survival until that moment.

Let us name this function $h(x)$, known as hazard rate function. The relationship between the hazard rate function with the distribution function and the survival function is the following:

$$h(x) = \frac{f(x)}{1-F(x)} = -\frac{S'(x)}{S(x)} \tag{2.5}$$

Thus, the survival probability could be expressed in terms of the hazard rate as:

$$S(t) = e^{-\int_0^t h(s)ds} \tag{2.6}$$

In addition to this, we define tq_x as the conditional probability that the asset will default within the next t years conditional on its survival for x years and tq_x as the conditional probability that the asset will survive within the next t years conditional on its survival for x years.

$$\begin{gathered} tq_x = Pr[T - x \leq t \mid T > x],\ t \geq 0 \\ tp_x = 1 - tq_x = Pr[T - x > t \mid T > x],\ t \geq 0 \end{gathered} \tag{2.7}$$

Now, , we can express $tp_x$and tq_x in terms of the hazard rates as follows:

$$\begin{aligned} tp_x &= e^{-\int_0^t h(s+x)ds} \\ tq_x &= 1 - e^{-\int_0^t h(s+x)ds} \end{aligned} \tag{2.8}$$

Furthermore,

$$F(t) = 1 - S(t) = 1 - e^{-\int_0^t h(s)ds} \tag{2.9}$$

And,

$$f(t) = S(t) \cdot h(t) \tag{2.10}$$

which is the density function for T.

A classical assumption, is to consider that the hazard rate, h, is constant over a certain period of time, defined by $[x, x+1]$. Therefore, the density function is:

$$f(t) = he^{-ht} \tag{2.11}$$

It shows that the survival time follows an exponential distribution with parameter h. Under this assumption, the survival probability over the time interval $[x, x+t]$ for $0 < t \leq 1$ is:

$$tp_x = 1 - tq_x = e^{-\int_0^t h(s)ds} = e^{-ht} = (p_x)^t \tag{2.12}$$

where p_x is the survival probability over 1 year. This assumption could also be used with a time interval of less than a year, always assuming a constant hazard rate for that interval. Therefore, by applying a hypothesis about CDS recovery, we can extract the probability of default from CDS prices.

To sum up, there are several reasons to use the hazard rate for modelling the probability of default. First, it gives us information about the instantaneous probability of default at time t of a firm, having survived until t. In second place, the hazard rate function could easily be applied in complex problems, where we need to introduce the dynamic of the default. Finally, there are a lot of similarities between interest rate and hazard rate, which is desirable.

2.3 Econometric models of credit spreads

Introduction

This section focuses on the estimates of credit spreads for issuers with no CDSs. As mentioned before the Basel Committee requires financial entities to establish credit spreads considering the rating, sector and region of the borrower. Furthermore, these credit curves will be decisive in pricing new assets in the banking book of a financial institution.

As we mentioned above, one of the most important problems that we find when estimating credit curves is the lack of reliable data in some combination of rating-sector-region, finding frequently outliers in the CDS distribution by rating sector. Thus, given the particular features of the CDS spread, is the OLS regression the optimal method to estimate credit spread curves? Or is it more efficient to use more robust estimators which are not so affected by the presence of outliers? Should we weight the information for rating, sector or region evenly? For a financial institution, it is clear that the best approach is that which reflects the market trend and minimizes the fluctuations of the estimates.

The analysed models in this chapter could be classified in two differentiated groups:

1. **Non-hierarchical regression**. We present the classical ordinary least-squares, OLS, regression as a possibility for estimating credit curves. In addition, in that subsection we introduce the quantile regression for the median as an alternative to the OLS model.

2. **Hierarchical regression**. Non-hierarchical regression models are often run using data with observations that are highly correlated within subsamples. Hierarchical models share the notion that individual observations are grouped in some way by the data design. For example, in the credit market we can use the rating, sector and region as factors to explain the observed credit spread for an issuer, and therefore, we can establish the order of these factors to explain the observed spread in this type of models.

2.3.1 Non-hierarchical regression

2.3.1.1 Ordinary least-squares regression (OLS)

Linear OLS regression

The initial basis model will be[1]

$$p_l = \beta_0 + \beta_1 R_{l,z} + \beta_2 S_{l,i} + \beta_3 G_{l,j} + \mu_l, \; l = 1,2,....L \tag{2.13}$$

where p_l represents the risk premium of the issuer l, and the variables R, S and G are dicotomic variables, representing the different levels of rating, sector, and geographical regions present in the sample. There are n variables R_z, m variables S_i, and k variables G_j, being n, m, and k the number of rating class, sectors, and geographical regions included in the sample. These variables are defined as

$R_{l,z} = 1$ if the CDS denoted by the subindex l has rating z, and $R_{l,z} = 0$ otherwise, for all $z = 1,2,...n$. In total, there are nine rating classes: AAA, AA, A, BBB, BB, B, CCC, D and NR (without rating).

[1] See Novales (2000) for more details of these models.

$S_{l,i} = 1$ if the CDS denoted by the subindex l corresponds to a firm that belongs to sector i, and $S_{l,i} = 0$ otherwise, for all $i = 1, 2, ...m$ .11 sectors are represented in the sample: Basic materials, consumer goods, consumer services, energy, financials, government, health care, industrials, technology, telecommunication services and utilities.

$G_{l,j} = 1$ if the CDS denoted by the subindex l corresponds to a company located in the geographical region j, and $G_{l,j} = 0$ otherwise, for all $j = 1, 2, ...k$. We have thirteen different regions in the sample: Africa, Asia, Caribbean, E.Eur, Europe, India, Lat.Amer, Middle East, N.Amer, Oceania, Offshore, Pacific and Supra.

In this case, we use senior 5-year CDS contracts (because of their representativeness), the currency and restructuring clause will be the standard one for each issuer, and the data contains the observations on 31 January 2012. In the first regression, the base regressors are the AAA rating, basic material sector, and Africa region. Such estimates are expressed as a decimal number, meaning that to show the results in basis points, it is necessary to multiply each coefficient by 10,000. The outcome is shown in Table 2.1 and the histogram of residuals in Figure 2.4. From these results, it can be observed that the influence of the coefficient rating regressors is as expected: the better the rating, the lower the coefficient. Furthermore, it is clear that there are significant differences among sector coefficients, the financial sector being more penalised than others, as the health care sector. Similarly, it occurs with region coefficients.

Table 2.1: Linear OLS regression on 31 January 2012

Coefficients	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	0.0086	0.0095	0.9	0.36	
AA	0.0018	0.0063	0.3	0.78	
A	0.0009	0.0060	0.1	0.88	
BBB	0.0076	0.0059	1.3	0.20	
BB	0.0277	0.0061	4.5	0.00	***
B	0.0585	0.0063	9.3	<2e-16	***
CCC	0.1678	0.0071	23.8	<2e-16	***
D	0.1462	0.0190	7.7	0.00	***
NR (1)	0.0150	0.0061	2.5	0.01	*
Consumer goods	-0.0036	0.0030	-1.2	0.23	
Consumer services	-0.0055	0.0031	-1.8	0.08	
Energy	-0.0032	0.0036	-0.9	0.38	
Financials	0.0107	0.0027	3.9	0.00	***
Government	-0.0020	0.0033	-0.6	0.55	
Health care	-0.0086	0.0041	-2.1	0.04	*
Industrials	-0.0001	0.0030	0.0	0.98	
Technology	-0.0033	0.0040	-0.8	0.41	
Telecommunication services	-0.0003	0.0038	-0.1	0.94	
Utilities	0.0000	0.0033	0.0	0.99	
Asia	-0.0008	0.0071	-0.1	0.91	
Caribbean	-0.0063	0.0120	-0.5	0.60	
E.Eur	0.0153	0.0080	1.9	0.05	.
Europe	0.0032	0.0070	0.5	0.65	
India	0.0123	0.0090	1.4	0.17	
Lat.Amer	0.0074	0.0079	0.9	0.35	
Middle East	0.0086	0.0081	1.1	0.29	
N.Amer	-0.0023	0.0070	-0.3	0.74	
Oceania	0.0026	0.0079	0.3	0.74	
Offshore	0.0171	0.0092	1.9	0.06	.
Supra	-0.0013	0.0150	-0.1	0.93	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.03124 on 2516 degrees of freedom Multiple R-squared: 0.4674, Adjusted R-squared: 0.4612, F-statistic: 76.12 on 29 and 2516 DF, p-value: < 2.2e-16

Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple each coefficient by 10,000.

(1) NR: Not rated

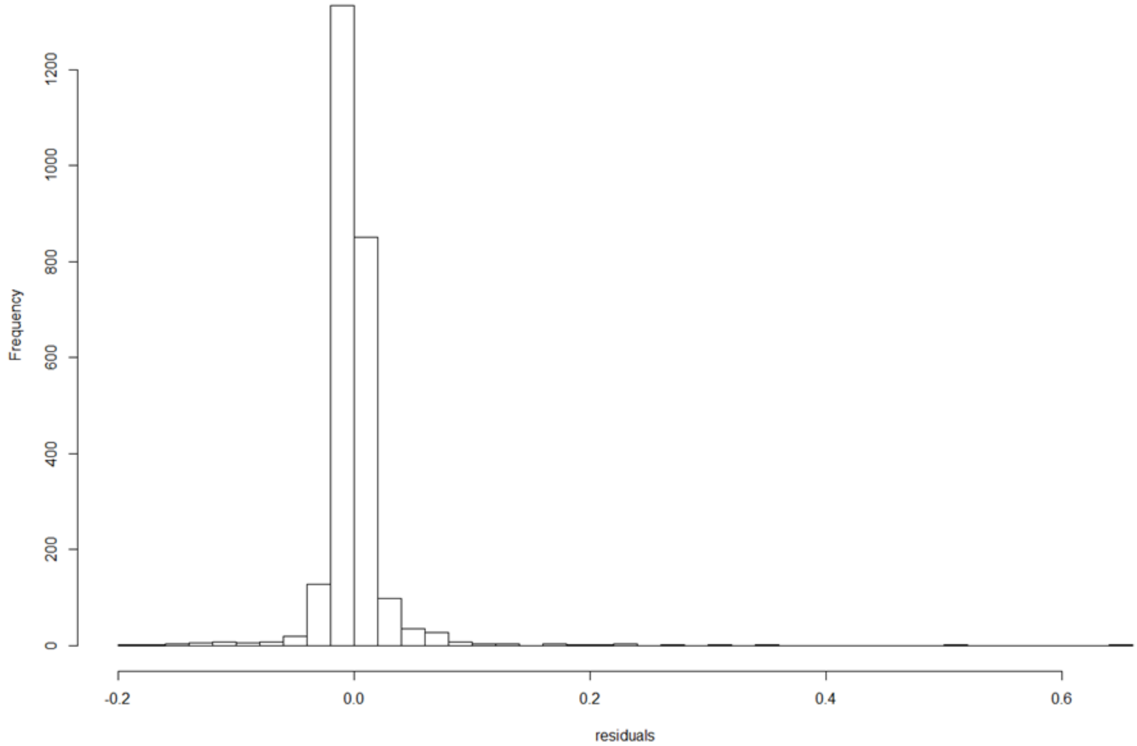
Exponential OLS regression

The second model represents the risk premium of a borrower as an exponential function of rating, sector and region.

Thus, let us denote:

$$p_l = \exp^{\beta_0+\beta_1 R_{l,z}+\beta_2 S_{l,i}+\beta_3 G_{l,j}+\mu_l},\ l = 1, 2, \ldots .L \tag{2.14}$$

Figure 2.4: Histogram of residuals of the linear OLS regression on 31 January 2012



where p_l represents the risk premium of the issuer l, and the variables R, S and G are dicotomic variables, representing the different levels of rating, sector, and geographical regions present in the sample. There are n variables R_z, m variables S_i, and k variables G_j, being n, m, and k the number of rating class, sectors, and geographical regions included in the sample. These variables are defined as

$R_{l,z} = 1$ if the CDS denoted by the subindex l has rating z, and $R_{l,z} = 0$ otherwise, for all $z = 1, 2, ...n$. In total, there are nine rating classes: AAA, AA, A, BBB, BB, B, CCC, D and NR (without rating).

$S_{l,i} = 1$ if the CDS denoted by the subindex l corresponds to a firm that belongs to sector i, and $S_{l,i} = 0$ otherwise, for all $i = 1, 2, ...m$ .11 sectors are represented in the sample: Basic materials, consumer goods, consumer services, energy, financials, government, health care, industrials, technology, telecommunication services and utilities.

$G_{l,j} = 1$ if the CDS denoted by the subindex l corresponds to a company located in the geographical region j, and $G_{l,j} = 0$ otherwise, for all $j = 1, 2, ...k$. We have thirteen different regions in the sample: Africa, Asia, Caribbean, E.Eur, Europe, India, Lat.Amer, Middle East, N.Amer, Oceania, Offshore, Pacific and Supra.

In this case, we again use senior 5-year CDS contracts. The currency and restructuring clause will be the standard ones for each issuer. The data contains the observations of 31 January 2012. In this first regressions, the base regressors are AAA rating, basic material sector, and Africa region. Such estimates are expressed as decimals, meaning that to show the result in basis points, it is necessary to multiply each coefficient by 10,000.

Table 2.2 shows the results of this model, using the same assumptions as before, and Figure 2.5 depicts the histogram of residuals . Indeed, the output for this second model has a great relationship with the previous one.

Table 2.2: Exponential OLS regression on 31 January 2012

Regressors	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	-4.9794	0.1870	-26.6	<2e-16	***
AA	0.3585	0.1238	2.9	0.00	**
A	0.4692	0.1174	4.0	0.00	***
BBB	0.8177	0.1166	7.0	0.00	***
BB	1.5576	0.1197	13.0	<2e-16	***
B	2.2286	0.1236	18.0	<2e-16	***
CCC	2.9149	0.1386	21.0	<2e-16	***
D	3.2168	0.3727	8.6	<2e-16	***
NR (1)	1.0082	0.1201	8.4	<2e-16	***
Consumer goods	-0.0998	0.0590	-1.7	0.09	
Consumer services	-0.0271	0.0605	-0.4	0.65	
Energy	0.0817	0.0700	1.2	0.24	
Financials	0.5049	0.0539	9.4	<2e-16	***
Government	0.1338	0.0644	2.1	0.04	*
Health care	-0.2715	0.0802	-3.4	0.00	***
Industrials	0.0684	0.0598	1.1	0.25	
Technology	0.0423	0.0776	0.5	0.59	
Telecommunication services	-0.0538	0.0742	-0.7	0.47	
Utilities	0.0405	0.0650	0.6	0.53	
Asia	-0.3055	0.1388	-2.2	0.03	*
Caribbean	-0.0127	0.2365	-0.1	0.96	
E.Eur	0.3640	0.1562	2.3	0.02	*
Europe	-0.0786	0.1384	-0.6	0.57	
India	0.4869	0.1766	2.8	0.01	**
Lat.Amer	0.1169	0.1552	0.8	0.45	
Middle East	0.2727	0.1588	1.7	0.09	.
N.Amer	-0.3542	0.1372	-2.6	0.01	**
Oceania	0.0525	0.1559	0.3	0.74	
Offshore	0.0506	0.1803	0.3	0.78	
Supra	0.0669	0.2948	0.2	0.82	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.6134 on 2516 degrees of freedom Multiple R-squared: 0.5343, Adjusted R-squared: 0.5289, F-statistic: 99.53 on 29 and 2516 DF, p-value: < 2.2e-16
Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple each coefficient by 10,000.

(1) NR: Not Rated

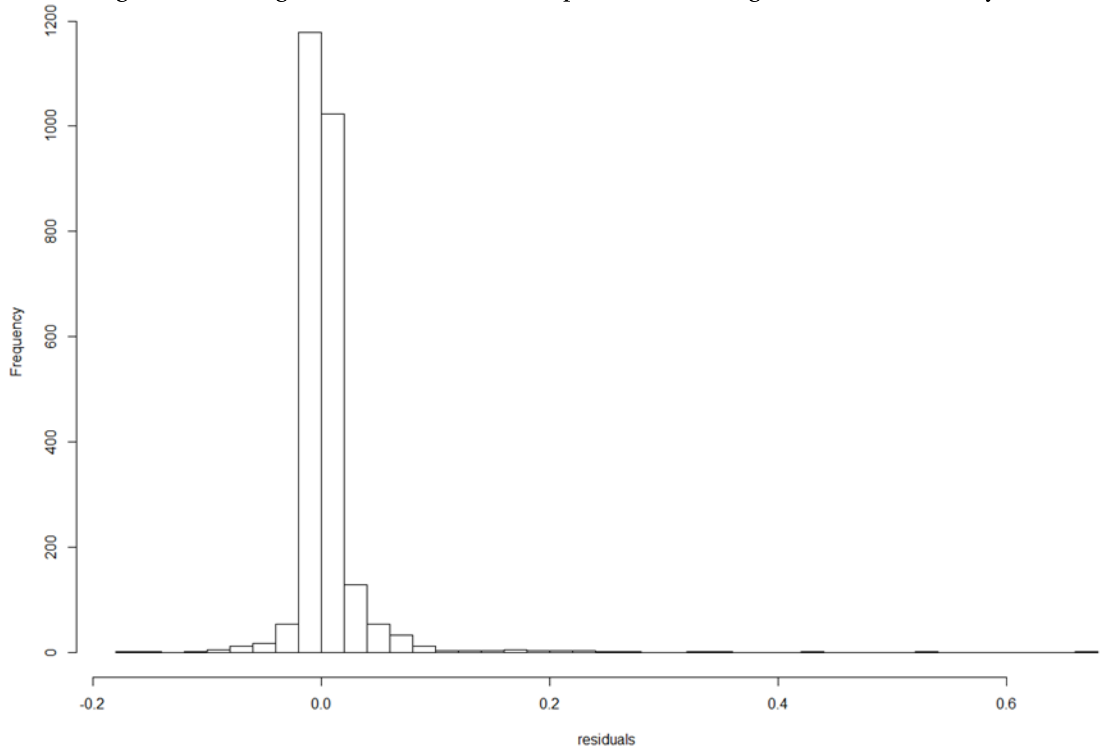
2.3.1.2 Quantile regression

Introduction

Is the OLS method the best approach to estimate a data regression? Are there better alternatives?

The comparison between the mean and the median has been widely studied in the past. Since the days

Figure 2.5: Histogram of residuals of the exponential OLS regression on 31 January 2012



of Gauss, it has been recognised that the mean is an optimal estimator if the residuals follow a normal distribution; therefore, under this hypothesis, the ordinary least-squares method is the best approach. However, in the presence of big outliers, as occurs with the distribution of credit spreads by a determined rating and sector, the median is a better estimator than the mean. These arguments were pointed out by Shiryayev (1992). Median regression is more robust to outliers than least-squares regression, and the median regression is semiparametric as it avoids assumptions about the parametric distribution of the error process [see Koenker and Machado (1999), Koenker (2001), Koenker (2005) and Koenker (2006)].

Analogous to the conditional mean function of linear regression, we may consider the relationship between regressors and outcome (y) using the conditional median function or quantile (q) of the empirical distribution. Quantile regression also provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of y, not merely its conditional mean. Thus, the quantile regression offers a more focused view of the problem than could be achieved by looking exclusively at conditional mean models. This method uses just “local” information around the conditional distribution in which we are interested. In addition to this, it avoids assumptions about the parametric distribution of the residuals. Median regression, also known as least-absolute-deviations (LAD) minimizes the sum of the absolute values of the residuals. For example, Moody’s uses this type of methodologies based on the median to estimate the credit spreads by rating and sector and implied rating [see, for example, Munves et al. (2007)].

The model for linear quantile regression is

$$y = X^{'}\beta + \mu \tag{2.15}$$

where $y = (y_1, ..., y_n)^{'}$ is the $(nx1)$ vector of responses, $X^{'} = (x_1, ..., x_n)^{'}$ is the (nxp) regressor matrix, $\beta^{'} = (\beta_1, ..., \beta_n)^{'}$ is the vector $(px1)$ of unknown parameters, and $\mu = (\mu_1, ..., \mu_n)^{'}$ is the $(nx1)$ vector of unknown errors.

L_1 regression, also known as median regression, is a natural extension of the sample median when the response is conditioned on the covariates. In L_1 regression, the least absolute residuals estimate $\hat{\beta}_{LAR}$, referred to as the L_1-norm estimate, is obtained as the solution of the minimization problem

$$\min_{\beta \epsilon R^p} \sum_{i=1}^{n} | y_i - x_i^{'}\beta | \tag{2.16}$$

More generally, for quantile regression Koenker and Bassett Jr (1978) defined the τth regression quantile, $0 < \tau < 1$, as any solution to the minimization problem

$$\min_{\beta \epsilon R^p} \left[\sum_{i \epsilon \left\{ i : y_i \geqslant x_i^{'}\beta \right\}} \tau | y_i - x_i^{'}\beta | + \sum_{i \epsilon \left\{ i : y_i < x_i^{'}\beta \right\}} (1-\tau) | y_i - x_i^{'}\beta | \right] \tag{2.17}$$

The solution is denoted as $\beta(\hat{\tau})$, and the L_1-norm estimate corresponds to $\hat{\beta}(1/2)$. The τth regression quantile is an extension of the τth sample quantile $\omega(\tau)$, which can be formulated as the solution of

$$\min_{\omega \epsilon R^p} \left[\sum_{i \epsilon \{ i : y_i \geqslant \omega \}} \tau | y_i - \omega | + \sum_{i \epsilon \{ i : y_i < \omega \}} (1-\tau) | y_i - \omega | \right] \tag{2.18}$$

Linear median regression

After the introduction of the quantile regression, we will look at the median regression to compare it with the previous results based on the mean. In the linear case, as we defined before:

$$p_l = \beta_0 + \beta_1 R_{l,z} + \beta_2 S_{l,i} + \beta_3 G_{l,j} + \mu_l, \; l = 1, 2, ...L \tag{2.19}$$

where p_l represents the risk premium of the issuer l, and the variables R, S and G are dicotomic variables, representing the different levels of rating, sector, and geographical regions present in the sample. There are n variables R_z, m variables S_i, and k variables G_j, being n, m, and k the number of rating class, sectors, and geographical regions included in the sample. These variables are defined as

$R_{l,z} = 1$ if the CDS denoted by the subindex l has rating z, and $R_{l,z} = 0$ otherwise, for all $z = 1, 2, ...n$. In total, there are nine rating classes: AAA, AA, A, BBB, BB, B, CCC, D and NR (without rating).

$S_{l,i} = 1$ if the CDS denoted by the subindex l corresponds to a firm that belongs to sector i, and $S_{l,i} = 0$ otherwise, for all $i = 1, 2, ...m$ .11 sectors are represented in the sample: Basic materials, consumer goods, consumer services, energy, financials, government, health care, industrials, technology, telecommunication services and utilities.

$G_{l,j} = 1$ if the CDS denoted by the subindex l corresponds to a company located in the geographical region j, and $G_{l,j} = 0$ otherwise, for all $j = 1, 2, ...k$. We have thirteen different regions in the sample: Africa, Asia, Caribbean, E.Eur, Europe, India, Lat.Amer, Middle East, N.Amer, Oceania, Offshore, Pacific and Supra.

Again, we use senior 5-year CDS contracts, because of their representativeness. The currency and restructuring clause will be the standard ones for each issuer. The data contains the observations of 31 January 2012. In this first regressions, the base regressors are AAA rating, basic material sector, and Africa region. Such estimates are expressed as decimals, meaning that to express the result in basis points, it is necessary to multiply each coefficient by 10,000.

Table 2.3 shows the coefficients of the median regression, and the histogram of residuals is shown in Figure 2.6. For this particular sample, the results from least-absolute-deviations method and OLS method are very similar in terms of the coefficients regressors, as well as the more representative statisticians. It would be interesting to analyse this outcome through time to extract conclusions. As we described in the Section 1.4 in the first chapter, the CDS spread is typically right-skewed; therefore, the median estimates will be usually lower and more robust than the mean.[2]

[2] Another approach, which is not discussed in this document, is the use of robust OLS regression.

Table 2.3: Linear median regression on 31 January 2012

Coefficients	Value	Std.Error	tvalue	Pr(>|t|)
(Intercept)	0.0091	0.0033	2.8	0.01
AA	0.0029	0.0017	1.6	0.10
A	0.0042	0.0017	2.5	0.01
BBB	0.0087	0.0017	5.2	0.00
BB	0.0257	0.0022	11.8	0.00
B	0.0513	0.0029	17.8	0.00
CCC	0.1458	0.0344	4.2	0.00
D	0.1584	0.0068	23.2	0.00
NR (1)	0.0101	0.0018	5.5	0.00
Consumer goods	-0.0010	0.0010	-1.0	0.31
Consumer services	-0.0010	0.0011	-0.9	0.36
Energy	0.0016	0.0011	1.4	0.15
Financials	0.0080	0.0010	8.3	0.00
Government	0.0011	0.0012	0.9	0.37
Health care	-0.0025	0.0012	-2.1	0.04
Industrials	0.0010	0.0011	0.9	0.35
Technology	0.0000	0.0016	0.0	1.00
Telecommunication services	-0.0014	0.0012	-1.1	0.26
Utilities	0.0015	0.0010	1.5	0.14
Asia	-0.0059	0.0028	-2.2	0.03
Caribbean	-0.0080	0.0056	-1.4	0.15
E.Eur	0.0130	0.0032	4.1	0.00
Europe	-0.0032	0.0028	-1.2	0.25
India	0.0125	0.0032	4.0	0.00
Lat.Amer	-0.0004	0.0031	-0.1	0.89
Middle East	0.0050	0.0033	1.5	0.13
N.Amer	-0.0068	0.0027	-2.5	0.01
Oceania	-0.0021	0.0029	-0.7	0.46
Offshore	-0.0022	0.0042	-0.5	0.59
Supra	-0.0035	0.0105	-0.3	0.74

Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple each coefficient by 10,000.

(1) NR: Not Rated

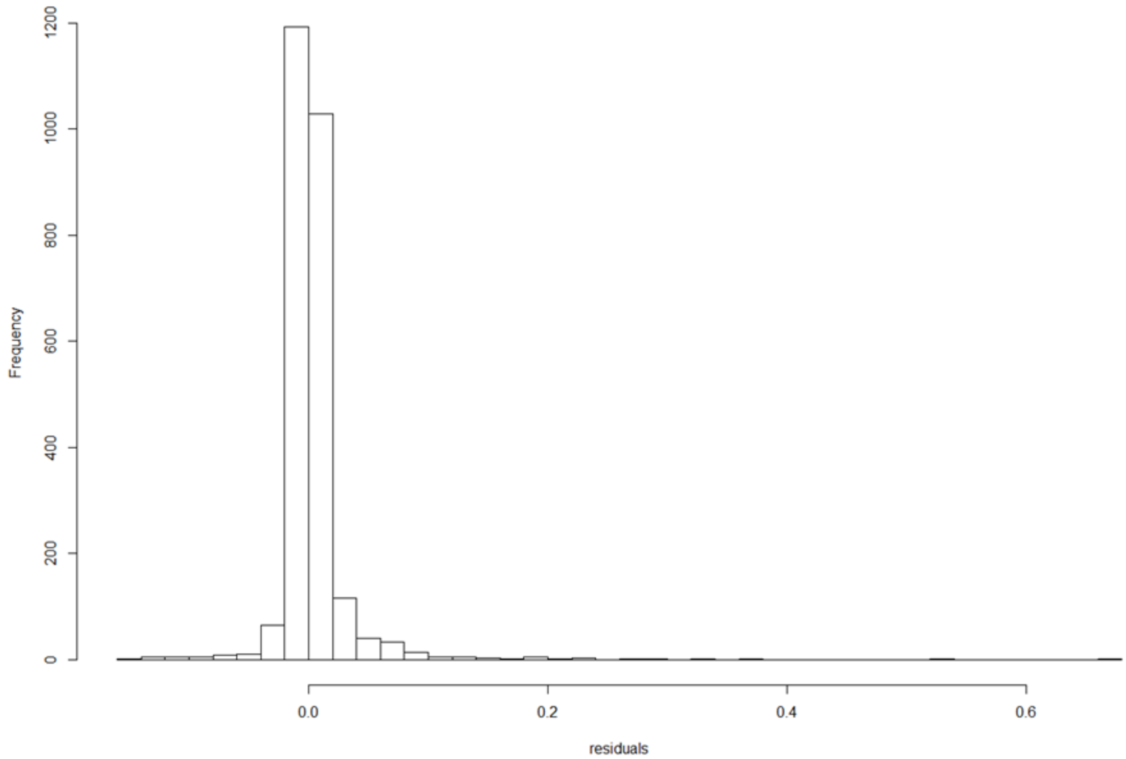
Exponential Median Regression

Finally, we present the exponential median regression as follows:

$$p_l = \exp^{\beta_0+\beta_1 R_{l,z}+\beta_2 S_{l,i}+\beta_3 G_{l,j}+\mu_l},\ l = 1, 2, ...L \tag{2.20}$$

where p_l represents the risk premium of the issuer l, and the variables R, S and G are dicotomic variables, representing the different levels of rating, sector, and geographical regions present in the sample. There are n variables R_z, m variables S_i, and k variables G_j, being n, m, and k the number of rating class, sectors, and geographical regions included in the sample. These variables are defined as

Figure 2.6: Histogram of residuals of the linear median regression on 31 January 2012



$R_{l,z} = 1$ if the CDS denoted by the subindex l has rating z, and $R_{l,z} = 0$ otherwise, for all $z = 1,2,...n$. In total, there are nine rating classes: AAA, AA, A, BBB, BB, B, CCC, D and NR (without rating).

$S_{l,i} = 1$ if the CDS denoted by the subindex l corresponds to a firm that belongs to sector i, and $S_{l,i} = 0$ otherwise, for all $i = 1,2,...m$ .11 sectors are represented in the sample: Basic materials, consumer goods, consumer services, energy, financials, government, health care, industrials, technology, telecommunication services and utilities.

$G_{l,j} = 1$ if the CDS denoted by the subindex l corresponds to a company located in the geographical region j, and $G_{l,j} = 0$ otherwise, for all $j = 1,2,...k$. We have thirteen different regions in the sample: Africa, Asia, Caribbean, E.Eur, Europe, India, Lat.Amer, Middle East, N.Amer, Oceania, Offshore, Pacific and Supra.

As with all previous exercises, we make the same assumptions, so we choose senior 5-year CDS contracts (because of their representativeness). The currency and restructuring clause will be the standard one for each issuer. The data contains the observations of 31 January 2012. In this first regressions, the base regressors are AAA rating, basic material sector, and Africa region. Such estimates are expressed as decimals, meaning that to express the result in basis points, it is necessary to multiply each coefficient by 10,000. As we expected, these results are in line with the Exponential OLS represented above for this particular day (see Table 2.4 and Figure 2.7).

Table 2.4: Exponential median regression on 31 January 2012

Coefficients	Value	Std.Error	tvalue	Pr(>|t|)
(Intercept)	-5.0697	0.1770	-28.6	0.00
AA	0.3584	0.1086	3.3	0.00
A	0.5589	0.1040	5.4	0.00
BBB	0.9441	0.1035	9.1	0.00
BB	1.7012	0.1107	15.4	0.00
B	2.3876	0.1172	20.4	0.00
CCC	3.1984	0.1539	20.8	0.00
D	3.2615	0.1982	16.5	0.00
NR (1)	0.9829	0.1139	8.6	0.00
Consumer goods	-0.1467	0.0746	-2.0	0.05
Consumer services	-0.0593	0.0765	-0.8	0.44
Energy	0.1252	0.0754	1.7	0.10
Financials	0.5293	0.0635	8.3	0.00
Government	0.1695	0.0785	2.2	0.03
Health care	-0.2431	0.0892	-2.7	0.01
Industrials	0.0932	0.0742	1.3	0.21
Technology	0.0211	0.1039	0.2	0.84
Telecommunication services	-0.0962	0.0863	-1.1	0.26
Utilities	0.1394	0.0756	1.8	0.07
Asia	-0.3396	0.1368	-2.5	0.01
Caribbean	-0.2143	0.3338	-0.6	0.52
E.Eur	0.3564	0.1482	2.4	0.02
Europe	-0.1074	0.1346	-0.8	0.43
India	0.4253	0.1514	2.8	0.01
Lat.Amer	0.0320	0.1492	0.2	0.83
Middle East	0.2551	0.1502	1.7	0.09
N.Amer	-0.3804	0.1332	-2.9	0.00
Oceania	0.0413	0.1470	0.3	0.78
Offshore	0.0612	0.2092	0.3	0.77
Supra	-0.1025	0.2318	-0.4	0.66

Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple each coefficient by 10,000.

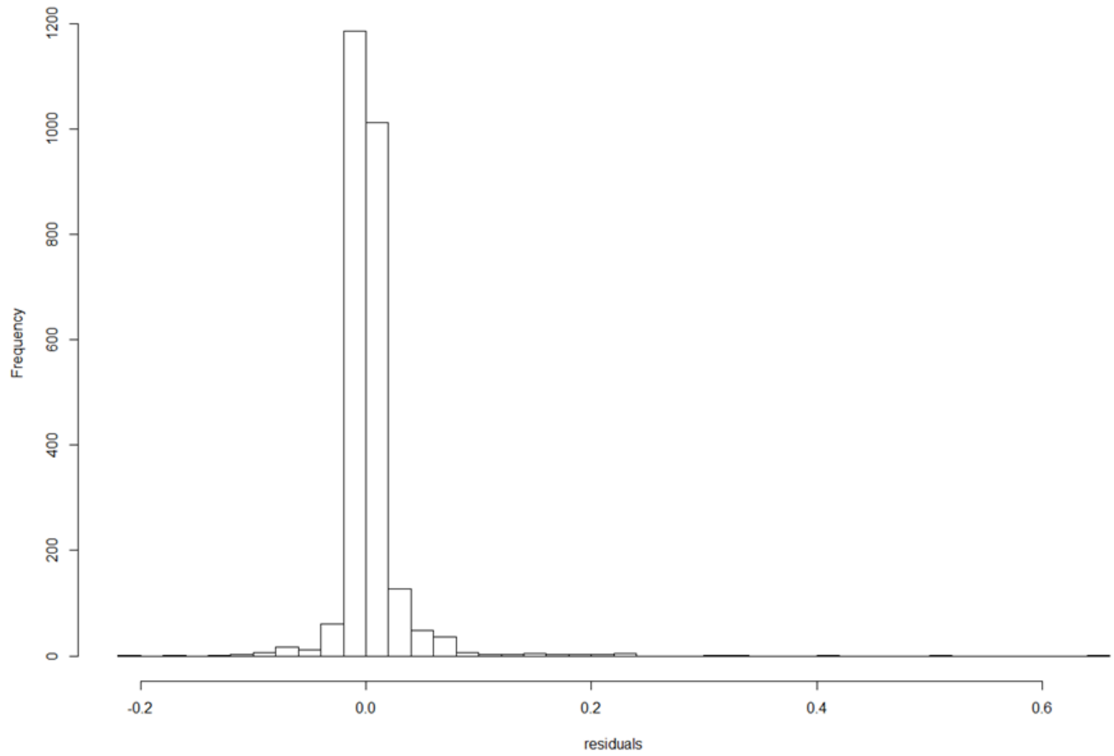
(1) NR: Not rated

2.3.2 Hierarchical regression, multilevel regression

Motivation

Are regression models (be the standard OLS regression or the median regression) the best approaches to estimate credit curves? The answer is probably no. Suppose we need to estimate the credit spread for an A-rating basic material borrower and an A-rating financial borrower, none of them having a CDS contract. Under a financial crisis scenario, it is easy to assume that the spread for an issuer of rating A in the basic material sector will be more in line with the rest of A-rating spreads in the market than the A-rating financial spread, which would be well above the sample mean. Hence, the A-rating financial spread estimated by an OLS regression or

Figure 2.7: Histogram of residuals of the exponential median regression on 31 January 2012



a median regression will probably be subsidized, as these models use all the available information on A-rating issues, even though the two borrowers for which we want to estimate an spread belong to different sectors.

In such situations, relatively frequent in the credit market, where the available sample of CDS spreads can be differentiated by ratings, sectors or regions, the OLS or median regression models are not optimal. The reason is that these type of models estimate an average credit spread by rating type, sector or region. Therefore, these models will penalize some determined homogeneous borrowers and they will subsidize others. As a way out of this difficulty, we propose the use of hierarchical regressions, also known as multilevel regression models, for these type of situations. They apply to cases in which a given sample can be naturally classified among subsamples, with observations being relatively homogeneous inside each subsample, while heterogeneity can be important across subsamples. In our sample, credit spreads can be expected to display a similar behaviour in a given sector, while experiencing different behaviour among different sectors. Something similar might be expected if we classify our sample of credit spreads according to rating levels, for instance. Hierarchical regressions are statistically more efficient precisely because they exploit the similarity among the observations that belong to the same subsample [see Snijders and Bosker (1999)].

Introduction

Hierarchical models consider the existence within the sample of different subsamples made up with relatively homogeneous observations. In that situation, more precise estimates can be obtained even if we allow for parameter variation over subsamples, since we will use a relatively homogeneous sample to estimate the parameters associated to each subsample. This is the strategy followed by hierarchical models. In general, assuming the existence of m subsamples, a basic cross-section regression of firm data with a single explanatory variable could be written for the N firms in the sample:

$$y_l = \alpha + \sum_{i=1}^{m} \beta_i X_l D_{l,i} + u_l,\ l = 1,2,....,N \tag{2.21}$$

Where $D_{l,i}$ is a dummy variable that takes the value 1 only if firm l is included in subsample i, and it is equal to zero otherwise. Now, we assume that the coefficient β_i, that measures the sensitivity of y_l to changes in X_l, depends on which of the m subsamples contains the $l-th$ observation:

$$\beta_i = \delta + \gamma' Z_i,\ i = 1,2,....,m \tag{2.22}$$

In this model, differences in β_i across sectors come from differences in sector characteristics Z_i. In (2.22) γ and Z_i are vectors with the same dimension. Vector Z_i will contain some variables that are specific of the i-th subsample. Suppose that firm l is included in the i_0 subsample. We will then end up with:

$$\begin{aligned} y_l &= \alpha + \beta_i X_l D_{l,i_0} + u_l = \alpha + (\delta + \gamma Z_{i_0}) X_l + u_l \\ &= \alpha + \delta X_l + (\gamma' Z_{i_0}) X_l + u_l,\ l = 1,2,....,N \end{aligned} \tag{2.23}$$

So that the effect of a unit change in X_l on y_l has a component that is common to all firms, and a second component that is specific of the subsample to which the firm belongs. Notice that y_l ends up being affected by variables (Z_i) that were not explicitly included in the original model.

If the intercept in the original regression also changes across subsamples, we would have:

$$y_l = \sum_{i=1}^{m} (\alpha_i D_{l,i} + \beta_i X_l D_{l,i}) + u_l,\ l = 1,2,....,N \tag{2.24}$$

With:

$$\begin{aligned} \alpha_i &= \mu + \lambda' W_i,\ i = 1,2,....,m \\ \beta_i &= \delta + \gamma' Z_i,\ i = 1,2,....,m \end{aligned} \tag{2.25}$$

Where some or all of the variables in vector W_i will be specific of the subsample i. The model then becomes:

$$y_l = \sum_{i=1}^{m} (\alpha_i D_{l,i} + \beta_i X_l D_{l,i}) + u_l = \sum_{i=1}^{m} [(\mu + \lambda' W_i) D_{l,i} + (\delta + \gamma' Z_i) X_l D_{l,i}] + u_l,\ l = 1,2,....,N \tag{2.26}$$

If firm l is included in subsample i_0, only one of the dummy variables above, D_{l,i_0} will be different from zero, and we will have:

$$\begin{aligned} y_l &= \alpha_{i_0} + \beta_{i_0} X_l + u_l = (\mu + \lambda' W_{i_0}) + (\delta + \gamma' Z_{i_0}) X_l + u_l \\ &= \mu + \lambda' W_{i_0} + \delta X_l + (\gamma' Z_{i_0}) X_l + u_l,\ l = 1,2,....,N \end{aligned} \tag{2.27}$$

To these specifications we could add the consideration that the functions that determine the values of coefficients α, and β have a stochastic additive term and are therefore random functions. That would produce different kinds of heteroskedastic structures in the error term of the final equation, which may be interesting in some applications. We do not consider that possibility in our analysis.

A simple situation arises when:

$$\begin{aligned} \alpha_i &= \mu + \lambda Z_i,\ i = 1,2,....,m \\ \beta_i &= \delta + \gamma Z_i,\ i = 1,2,....,m \end{aligned} \tag{2.28}$$

leading to model:

$$y_l = \left(\mu + \lambda Z_{i_0}\right) + \left(\delta + \gamma Z_{i_0}\right) X_l + u_l,\ l = 1,2,....,N \tag{2.29}$$

in which the slope and possibly the intercept are functions of a variable Z.

This description corresponds to a two-level hierarchical model, with the response of y_l to X_l being a function of characteristics of the subsamples defined by the different values of i. A three-level model would arise if we allowed for some of the coefficients λ, γ to depend on characteristics of subsamples defined by a different classification of the sample data.

2.3.2.1 One-level hierarchical model for credit spreads

Having introduced the hierarchical regression, we now want to use that framework to determine which variable, rating, sector, or region, is the most important factor in the determination of credit spreads. In our previous analysis, based on simple regressions, we have seen the rating to be the most influential variable in the CDS price through time. Thus, we start with the specification:

$$p_l = \alpha + \beta R_l + \mu_l, l = 1,2,....L \tag{2.30}$$

Where p_l is the credit spread for firm l, and R_l is its rating. The one-level hierarchical model is just a standard linear regression model.[3]

[3] If we use the median estimate, we get the same results of the median regression.

2.3.2.2 Two-level hierarchical model for credit spreads

Our model has the peculiarity that the explanatory variable, rating, is defined by a set of dummy variables $R_{l,z}$, where $R_{l,z}$=1 if firm l has rating z, being equal to zero otherwise.

Hence, assuming there are n different ratings in the sample, the model can be more precisely formulated as:

$$p_l = \alpha + \sum_{z=1}^{n} \beta_z R_{l,z} + \mu_l,\ l = 1,2,....L \tag{2.31}$$

For each firm l, there will be just one value of the z-index, $z_0$say, for which R_{l,z_0}=1, thus, having for that firm:

$$p_l = \alpha + \beta_{z_0} + \mu_l, \tag{2.32}$$

which is a model where credit spread has a component that is common to all firms in the sample, and a second component that is specific of the level of rating, but it is the same for all firms with the same rating. Therefore, this model assigns the same level of credit spread to all firms with the same level of rating.

As in the general description above, the two-level hierarchical model for credit spreads arises when we allow the coefficients in the model to depend on a sample partition. In our application, we will consider the partition defined by the different sectors. For simplicity, we will assume in this presentation that only the slope varies across sectors and regions.

So, letting the rating slope in the credit spread equation to change across sectors $i = 1,2,...,m$,

$\beta_z = \delta_z + \gamma_{z,i}, i = 1,2,...,m$

we would have:

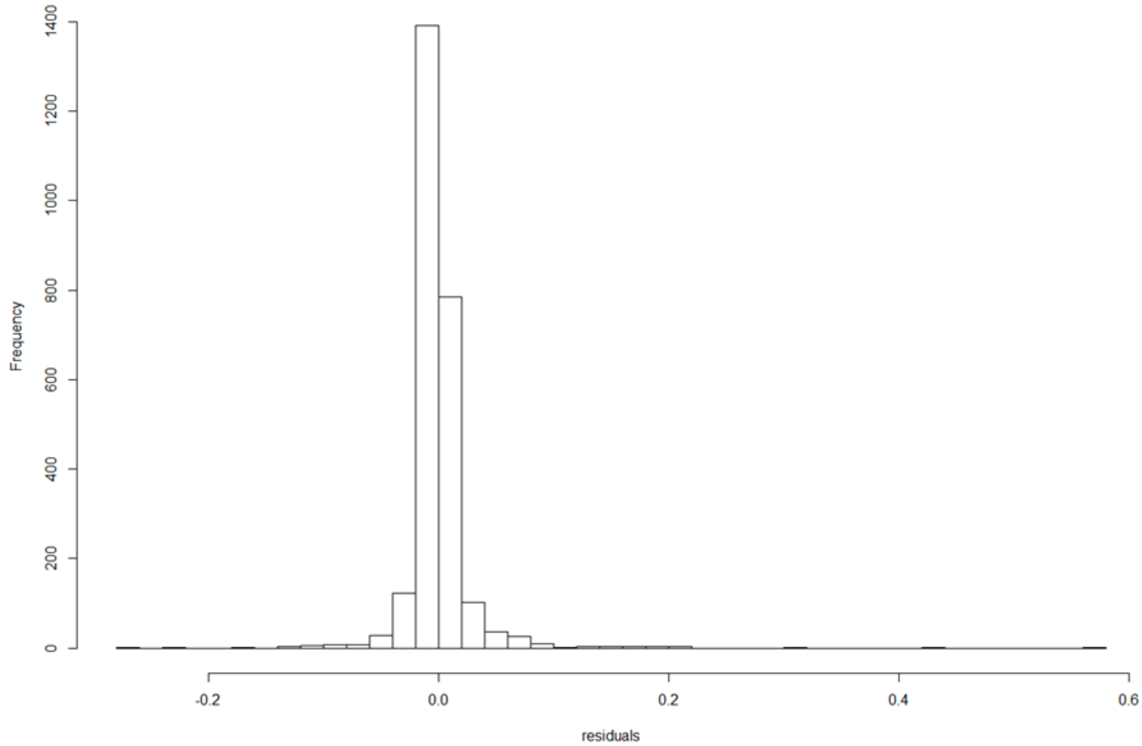
$$p_l = \alpha + \sum_{i=1}^{m} \sum_{z=1}^{n} \beta_z R_{l,z} S_{l,i} + u_l = \alpha + \textstyle\sum_{z=1}^{n} (\delta_z + \gamma_{z,i_0}) R_{l,z} + u_l,\ l = 1,2,....,L \tag{2.33}$$

with dummy variables $S_{l,i}$ being defined by $S_{l,i}$=1 if firm l belongs to sector i, being equal to zero otherwise, and we have assumed that firm l belongs to sector i_0. If firm l has rating z_0, then we will have:

$$p_l = \alpha + (\delta_{z_0} + \gamma_{z_0,i_0}) + u_l,\ l = 1,2,....,L \tag{2.34}$$

In this two-level model, the credit sector has a component that is common to all firms in the sample, a second component that is specific of each level of rating, and a third component that is different for each pair (rating, sector). At a difference from the previous model, given two firms with the same rating, the model will assign them a different credit spread, depending on the sector to which they belong. However, firms with the

Figure 2.8: Histogram of residuals of the mean two-level hierarchical regression on 31 January 2012



same rating in the same sector will be assigned the same credit spread.

This is the model estimated in Tables 2.5 and 2.6, and the histogram of residuals is shown in Figure 2.8 . To avoid the trap of singularity, we estimate the model excluding the dummy variable for a level of rating (AAA) that it is taken as reference, as well as excluding the dummy variable for one of the sectors (basic materials). As in all previous exercises, we choose the senior 5-year CDS contract, because of their representativeness. The currency and restructuring clause will be the standard one for each issuer. For a first example, we select the data for January 31, 2012. Estimates are expressed as decimals, meaning that to express the result in basis points, it is necessary to multiply each coefficient by 10,000.

Other two-level models would be possible, using the region instead of the sector. So, letting the rating slope in the credit spread equation to change across regions $\beta_z = \delta_z + \gamma_{z,j}$, $j = 1, 2, ..., k$, we would have:

$$p_l = \alpha + \sum_{j=1}^{j} \sum_{z=1}^{n} \beta_z R_{l,z} G_{l,j} + u_l, \; l = 1, 2, ..., L \tag{2.35}$$

with dummy variables $G_{l,j}$ being defined by $G_{l,j}$=1 if firm l belongs to region j, being equal to zero otherwise. If firm l belongs to region j_0,we would have:

$$p_l = \alpha + \sum_{z=1}^{n} (\delta_z + \gamma_{z,j_0}) R_{l,z} + u_l, \; l = 1, 2, ..., L \tag{2.36}$$

and if that firm l has rating z_0, then we will end up with credit spread being characterized as:

Table 2.5: Mean two-level hierarchical regression on 31 January 2012. (Part I)

Coefficients	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	0.0041	0.0195	0.2	0.83	
AA	0.0065	0.0206	0.3	0.75	
A	0.0044	0.0199	0.2	0.82	
BB	0.0094	0.0197	0.5	0.63	
BB	0.0253	0.0201	1259.0	0.21	
B	0.1008	0.0218	4614.0	0.00	***
CCC	0.2786	0.0276	10082.0	<2e-16	***
NR (1)	0.0053	0.0209	0.3	0.80	
AA:Consumer goods	-0.0051	0.0090	-0.6	0.57	
A:Consumer goods	-0.0017	0.0051	-0.3	0.74	
BBB:Consumer goods	-0.0020	0.0037	-0.5	0.59	
BB:Consumer goods	0.0030	0.0062	0.5	0.63	
B:Consumer goods	-0.0523	0.0109	-4787.0	0.00	***
CCC:Consumer goods	-0.0983	0.0218	-4503.0	0.00	***
NR:Consumer goods	0.0006	0.0104	0.1	0.96	
AA:Consumer services	-0.0046	0.0092	-0.5	0.62	
A:Consumer services	-0.0010	0.0064	-0.2	0.87	
BBB:Consumer services	-0.0013	0.0037	-0.4	0.73	
BB:Consumer services	0.0070	0.0058	1194.0	0.23	
B:Consumer services	-0.0438	0.0106	-4122.0	0.00	***
CCC:Consumer services	-0.1930	0.0209	-9242.0	<2e-16	***
NR:Consumer services	0.0112	0.0092	1218.0	0.22	
AAA:Energy	-0.0004	0.0239	0.0	0.99	
AA:Energy	-0.0023	0.0098	-0.2	0.82	
A:Energy	0.0003	0.0062	0.0	0.97	
BBB:Energy	0.0020	0.0039	0.5	0.60	
BB:Energy	-0.0053	0.0077	-0.7	0.49	
B:Energy	-0.0480	0.0138	-3477.0	0.00	***
AAA:Financials	0.0053	0.0276	0.2	0.85	
AA:Financials	0.0079	0.0074	1073.0	0.28	
A:Financials	0.0111	0.0044	2555.0	0.01	*
BBB:Financials	0.0106	0.0036	3.0	0.00	**
BB:Financials	0.0183	0.0064	2855.0	0.00	**
B:Financials	-0.0315	0.0131	-2405.0	0.02	*
CCC:Financials	-0.1045	0.0211	-4953.0	0.00	***
NR:Financials	0.0194	0.0096	2018.0	0.04	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Residual standard error: 0.01954 on 1279 degrees of freedom
Multiple R-squared: 0.5978 Adjusted R-squared: 0.5745 F-statistic: 25.69 on 74 and 1279 DF, p-value: < 2.2e-16

Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple by10,000 each coefficient.

(1) NR: Not rated

Table 2.6: Mean two-level hierarchical regression on 31 January 2012 (Part II)

Coefficients	Estimate	Std.Error	tvalue	Pr(>|t|)	
AAA:Government	0.0051	0.0203	0.3	0.80	
AA:Government	0.0034	0.0092	0.4	0.72	
A:Government	0.0134	0.0056	2382.0	0.02	*
BBB:Government	0.0143	0.0044	3245.0	0.00	**
BB:Government	0.0217	0.0087	2488.0	0.01	*
B:Government	-0.0429	0.0131	-3275.0	0.00	**
CCC:Government	-0.2060	0.0276	-7454.0	0.00	***
NR:Government	0.0072	0.0089	0.8	0.42	
AA:Health care	-0.0055	0.0109	-0.5	0.61	
A:Health care	-0.0023	0.0058	-0.4	0.70	
BBB:Health care	-0.0053	0.0068	-0.8	0.44	
BB:Health care	0.0054	0.0092	0.6	0.56	
B:Health care	-0.0671	0.0131	-5121.0	0.00	***
NR:Health care	0.0887	0.0209	4246.0	0.00	***
AA:Industrials	-0.0027	0.0130	-0.2	0.83	
A:Industrials	0.0007	0.0050	0.1	0.90	
BBB:Industrials	0.0009	0.0038	0.2	0.80	
BB:Industrials	0.0014	0.0059	0.2	0.81	
B:Industrials	-0.0547	0.0116	-4.7	0.00	***
CCC:Industrials	-0.1302	0.0276	-4711.0	0.00	***
NR:Industrials	0.0154	0.0098	1561.0	0.12	
AA:Technology	-0.0055	0.0206	-0.3	0.79	
A:Technology	0.0010	0.0069	0.1	0.89	
BBB:Technology	0.0025	0.0052	0.5	0.64	
BB:Technology	0.0063	0.0083	0.8	0.45	
B:Technology	-0.0329	0.0126	-2607.0	0.01	**
CCC:Technology	-0.2041	0.0276	-7387.0	0.00	***
NR:Technology	0.0079	0.0157	0.5	0.61	
AA:Telecommunication services	-0.0028	0.0117	-0.2	0.81	
A:Telecommunication services	0.0004	0.0058	0.1	0.94	
BBB:Telecommunication services	0.0048	0.0050	1.0	0.34	
BB:Telecommunication services	0.0147	0.0087	1692.0	0.09	.
B:Telecommunication services	-0.0289	0.0126	-2294.0	0.02	*
NR:Telecommunication services	0.0432	0.0122	3528.0	0.00	***
A:Utilities	0.0028	0.0051	0.5	0.59	
BBB:Utilities	0.0006	0.0041	0.2	0.88	
BB:Utilities	0.0055	0.0092	0.6	0.55	
B:Utilities	0.0170	0.0122	1386.0	0.17	
NR:Utilities	0.0009	0.0157	0.1	0.96	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Residual standard error: 0.01954 on 1279 degrees of freedom
Multiple R-squared: 0.5978 Adjusted R-squared: 0.5745 F-statistic: 25.69 on 74 and 1279 DF, p-value: < 2.2e-16

Note: These estimates are expressed as decimals, it means that to get the result in basis points, it is necessary to multiple by10,000 each coefficient.

(1) NR: Not rated

$$p_l = \alpha + (\delta_{z_0} + \gamma_{z_0,j_0}) + u_l,\ l = 1,2,....,L \tag{2.37}$$

In this two-level model, the credit sector has a component that is common to all firms in the sample, a second component that is specific of each rating and a third component that is different for each pair (rating, region). Given two firms with the same rating, the model will assign them a different credit spread, depending on the region to which they belong. Firms with the same rating in the same region will be assigned the same credit spread.

The question that arises in this context is whether we should use using the sector or the region as a second level in the hierarchical model. In our opinion there are two arguments in favour of using the sector as the second factor instead of the region:

1. The first reason is the economic globalisation. Companies operating in the credit corporate world are more globalized each day which makes the results of multinational companies to be very affected by the situation of their respective sector. As a consequence, the decision by the agency rating when analysing the solvency of a corporate company will increasingly depend on the company sector and more marginally on its region. With all these approximations we depart from hierarchical models.

2. The structure of the credit market data itself. There are several credit classes, defined by a pair (rating, region), for which we do not have any available data (see Tables 2.7 and 2.8). That is, indeed, the case for the AA Africa class, precluding the possibility of estimating credit spreads for such (rating, region) pairs. We have more data available across the different classes composed by (rating; sector), as the next two tables show, so that it is more often feasible to estimate the two-level hierarchical model in (rating, sector) than in (rating, region).

Table 2.7: Rating-sector classification on 31 January 2012

Rating	Basic materials	Consumer goods	Consumer services	Energy	Financials	Government	Health care	Industrials	Technology	Telecommunication services	Utilities	Total
AAA				3	2	10	1	1	1			18
AA		9	9	7	22	16	8	3	2	3	9	88
A	24	42	22	20	129	20	18	40	9	25	33	382
BBB	51	63	71	55	101	35	14	74	25	21	54	564
BB	21	31	28	8	20	8	6	33	6	11	6	178
B	3	15	23	4	6	5	6	8	7	5	5	87
CCC	1	3	9		4	1		2	1		3	24
D					1							1
Total	100	163	162	97	285	95	53	161	51	65	110	1342
%/Total	7.45%	12.15%	12.07%	7.23%	21.24%	7.08%	3.95%	12.00%	3.80%	4.84%	8.20%	100.00%

Note: For this classification we have used all the data with a Markit quality rating higher than BB.

Table 2.8: Rating-region classification on 31 January 2012

Rating	Africa	Asia	Caribbean	E.Eur	Europe	India	Lat.Amer	Middle East	N.Amer	Oceania	Offshore	Supra	Total
AAA		1			8				8	1			18
AA		35			25		1	4	18	5			88
A		93	1	4	116		4	9	137	17	1		382
BBB	4	87		16	145	7	12	4	273	11	5		564
BB	2	28	1	4	48	1	1	2	89	1	1		178
B	1	4		2	20		2	1	56	1			87
CCC					3		1		19			1	24
D									1				1
Total	7	248	2	26	365	8	21	20	601	36	7	1	1342
%/Total	0.52%	18.48%	0.15%	1.94%	27.20%	0.60%	1.56%	1.49%	44.78%	2.68%	0.52%	0.07%	100%

Note: For this classification we have used all the data with a Markit quality rating higher than BB.

2.3.2.3 Three-level hierarchical model for credit spreads

The three-level hierarchical model arises when parameter values in the two-level hierarchical model are assumed to be a function of another variable that also introduces a classification of the sample observations. In our case, that might be the geographical region to which the issuer belongs.

So, returning to our initial model:

$$p_l = \alpha + \sum_{z=1}^{n} \beta_z R_{l,z} + \mu_l,\ l = 1,2,....L \tag{2.38}$$

and letting the rating slope in the credit spread equation to change across sectors $\beta_z = \delta_z + \gamma_{z,i}, i = 1,2,...,m$, as before. We now consider the possibility that the sector-specific component of β_z changes with the region:

$$\gamma_{z,i} = \vartheta_{z,i} + \rho_{z,i,j},\ j = 1,2,...,k \tag{2.39}$$

we would have:

$$p_l = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{m}\sum_{z=1}^{n} \beta_i R_{l,z} S_{l,i} G_{l,j} + u_l = \alpha + \sum_{j=1}^{k}\sum_{z=1}^{n} (\delta_z + \gamma_{z,i_0}) R_{l,z} + u_l = \tag{2.40}$$

$$= \alpha + \sum_{z=1}^{n} (\delta_z + \vartheta_{z,i_0} + \rho_{z,i_0,j_0}) R_{l,z} + u_{l,\, l=1,2,....L} \tag{2.41}$$

where we have assumed that firm l belongs to sector i_0 and region j_0. If, in addition, firm l has rating z_0, the model will predict a credit spread:

$$p_l = \alpha + (\delta_{z_0} + \vartheta_{z_0,i_0} + \rho_{z_0,i_0,j_0}) + u_l,\ l = 1,2,....L \tag{2.42}$$

having a first component that is common to all firms in the sample, a second component that is specific of each level of rating, a third component that differs for each pair (rating, sector) and a fourth component that is different for each trio (rating, sector, region).

The number of estimated coefficient will depend on the way how we specify the dummy variables to avoid the trap of perfect multicollinearity. If we include a constant intercept, then we will need to exclude one of the parameters in the three classes in the parenthesis above, thereby estimating $n + mn + mnk - 2$ different parameters.

Three-level hierarchical model for credit spreads without CDS data

As we mentioned before, the lack of data is very common in some combination of rating, sector and region, being impossible to apply equation (2.42). Suppose that we lack data for some of the combinations (rating z_0, sector i_0, region j_0).

Two-level (rating, sector) model with adjustment by (sector, region)

One possibility would then be to consider and letting the rating slope in the credit spread equation to change across sectors $\beta_z = \delta_z + \gamma_{z,i}$, $i = 1,2,...,m$, as before. We now consider the possibility that the sector-specific component of β_z changes with the region:

$$\gamma_{z,i} = \vartheta_{i,j} + \rho_{z,i,}\ j = 1,2,...,k \tag{2.43}$$

we would have:

$$p_l = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{m}\sum_{z=1}^{n}\beta_i R_{l,z} S_{l,i} G_{l,j} + u_l = \alpha + \sum_{j=1}^{k}\sum_{z=1}^{n}(\delta_z + \gamma_{z,i_0}) R_{l,z} + u_l = \tag{2.44}$$

$$= \alpha + \vartheta_{i_0,j_0} + \sum_{z=1}^{n}(\delta_z + \rho_{z,i_0}) R_{l,z} + u_{l,\, l=1,2,....L} \tag{2.45}$$

where we have assumed that firm l belongs to sector i_0 and region j_0. If, in addition, firm l has rating z_0, the model will predict a credit spread:

$$p_l = \alpha + (\delta_{z_0} + \vartheta_{i_0,j_0} + \rho_{z_0,i_0}) + u_l,\ l = 1,2,....L \tag{2.46}$$

having a first component that is common to all firms in the sample, a second component that is specific of each level of rating, a third component that differs for each pair (sector, region) and a fourth component that is different for each pair (rating, sector).

Two-level (rating, sector) model with adjustment by (rating, region)

One possibility would then be to consider and letting the rating slope in the credit spread equation to change across sectors $\beta_z = \delta_z + \gamma_{z,i}$, $i = 1,2,...,m$, as before. We now consider the possibility that the sector-specific component of β_z changes with the region:

$$\gamma_{z,i} = \vartheta_{z,j} + \rho_{z,i}\ j = 1,2,...,k \tag{2.47}$$

we would have:

$$p_l = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{m}\sum_{z=1}^{n} \beta_i R_{l,z} S_{l,i} G_{l,j} + u_l = \alpha + \sum_{j=1}^{k}\sum_{z=1}^{n} (\delta_z + \gamma_{z,i_0}) R_{l,z} + u_l = \tag{2.48}$$

$$= \alpha + \sum_{z=1}^{n} (\delta_z + \vartheta_{z,j_0} + \rho_{z,i_0}) R_{l,z} + u_l,\ l = 1,2,....L \tag{2.49}$$

where we have assumed that firm l belongs to sector i_0 and region j_0. If, in addition, firm l has rating z_0, the model will predict a credit spread:

$$p_l = \alpha + (\delta_{z_0} + \vartheta_{z_0,j_0} + \rho_{z_0,i_0}) + u_l,\ l = 1,2,....L \tag{2.50}$$

having a first component that is common to all firms in the sample, a second component that is specific of each level of rating, a third component that differs for each pair (rating, region) and a fourth component that is different for each pair (rating, sector).

Two-level (rating, sector) model with adjustment by region

We now consider the possibility that we also lack data for some pairs (rating, region). Let us then assume that the sector-specific component of β_z changes with the region as in:

$\gamma_{z,i} = \vartheta_j + \rho_{z,i}\ j = 1,2,...,k$

we would then have:

$$p_l = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{m}\sum_{z=1}^{n} \beta_i R_{l,z} S_{l,i} G_{l,j} + u_l = \alpha + \sum_{j=1}^{k}\sum_{z=1}^{n} (\delta_z + \gamma_{z,i_0}) R_{l,z} + u_l = \tag{2.51}$$

$$= \alpha + \vartheta_{j_0} + \sum_{z=1}^{n} (\delta_z + \rho_{z,i_0}) R_{l,z} + u_l,\ l = 1,2,....L \tag{2.52}$$

where we have assumed that firm l belongs to sector i_0 and region j_0. If, in addition, firm l has rating z_0, the model will predict a credit spread:

$$p_l = \alpha + \vartheta_{j_0} + (\delta_{z_0} + \rho_{z_0,i_0}) + u_l,\ l = 1,2,....L \tag{2.53}$$

having a first component that is common to all firms in the sample, a second component that is specific of each region (it is the same for all firms in a given region), a third component that is the same for all firms with the same rating and a fourth component that is different for each pair (rating, sector). The estimate of ϑ_{j_0} will be an average of the residuals that would be obtained by explaining credit spread by using rating through the δ_{z_0} term, and the cross (rating, sector) information through the ρ_{z_0,i_0} term. If a constant was included in this latter model, the estimate of ϑ_{j_0} might be positive or negative.

Two-level (rating, sector) model with adjustment by country

In some situations, the adjustment by region through the ϑ_{j_0} term might be considered too broad. If we have enough country data, we could make the adjustment by country. Assuming that the sector-specific component of β_z changes with the country as in:

$\gamma_{z,i} = \vartheta_w + \rho_{z,i}\ j = 1, 2, ..., k$

we would end up with an estimate for credit spread:

$$p_l = \alpha + \vartheta_{w_0} + (\delta_{z_0} + \rho_{z_0,\,i_0}) + u_l,\ l = 1, 2, ...L \tag{2.54}$$

where we have assumed that firm l has rating z_0, it belongs to sector i_0 and to country w_0.

The credit spread would then have a first component that is common to all firms in the sample, a second component that is specific of each country, a third component that is specific of each level of rating, and a fourth component that is different for each pair (rating, sector). The numerical estimate of ϑ_{w_0} would be the mean residual obtained when explaining credit spreads by rating and by the combination (rating, sector). Two more observations that we have in fact used in our estimations:

1. we could use a quantile regression approach with hierarchical models to estimate the mean effects of rating, sector and geographical region, the median effects, or effects on other parts of the sample distribution of CDS spreads,
2. hierarchical models could also be specified as an exponential function, resulting:

$$p_l = \exp(\alpha + \delta_{z_0} + \vartheta_{z_0,i_0} + \rho_{z_0,\,i_0,,j_0}) + u_l,\ \ l = 1, 2, ...L \tag{2.55}$$

As an example, we show the region median differentials ϑ_{j_0} calculated as the median for a region j of the difference between the credit spread for an issuer l that belongs to region j and the risk premium estimated with $p_l = \alpha + \vartheta_{j_0} + (\delta_{z_0} + \rho_{z_0,\,i_0}) + u_l, l = 1, 2, ..., L$ in Table 2.9. Finally, we present the country median differentials ϑ_{w_0} calculated as the mean residual for a country w_0 of the difference between the credit spread for an issuer l that belongs to country w_0 and the risk premium estimated with the mentioned equation in Table 2.10. Large country differentials relative to other countries in the same region might be anticipating rating changes as in the cases of Spain and Italy.

Table 2.9: Region median differentials (basis points) in May 2012

Differentials (basis points) on 16 May 2012					Differentials (basis points) on 28 May 2012				
Region	Dif.1y	Dif.3y	Dif.5y	Dif.10y	Region	Dif.1y	Dif.3y	Dif.5y	Dif.10y
Asia	-1	-5	-7	-10	Asia	-3	-6	-8	-12
E.Eur	48	47.5	56	51	E.Eur	45	54.5	49	42
Europe	17	23	20	11	Europe	22.5	23	19	13.5
Lat.America	9	17	9	12	Lat.America	7	15.5	6	2.5
Middle East	33	21	19	18	Middle East	30	23	17	16
N.Amer	-4	-5	-5	-4	N.Amer	-4	-6	-7	-6
Oceania	6,5	11	14	16.5	Oceania	10	11	21	26
Offshore	5.5	5.5	-0.5	3.5	Offshore	-3	-9	-5	-2

Note: Region median differentials calculated as the median for a region k of the difference between the CDS price for an issuer l belongs to region k and the premium risk estimated with equation (2.37).

Table 2.10: Country median differentials (basis points) in May 2012

Differentials (basis points) on 16 May 2012					Differentials (basis points) on 28 May 2012				
Country	Dif.1y	Dif.3y	Dif.5y	Dif.10y	Country	Dif.1y	Dif.3y	Dif.5y	Dif.10y
Australia	6.5	11	14	16.5	Australia	10	11	21	26
Bermuda	45	52	55	63	Bermuda	43	52	53	56
Canada	-9	-12.5	-12	-14	Canada	-8.5	-13.5	-15	-15
Finland	4.5	11.5	11.5	2.5	Finland	3.5	11	12	2.5
France	36	60	60	55	France	39	63	63	57
Germany	10	12	11	3	Germany	16	18	14	8
Hong Kong	6.5	12	19.5	25.5	Hong Kong	11	16	24	28
Italy	256.5	273.5	257	228.5	Italy	271	282	256	219
Japan	-2.5	-5	-8.5	-18	Japan	-4	-7.5	-8.5	-16.5
Korea (Republic of)	6	-6	-1	0	Korea (Republic of)	12	-4	0	0
Luxembourg	-3	-4	26	39	Luxembourg	-6	-5	26	35
Malaysia	6	-3	0	3	Malaysia	11	-1	1	4
Netherlands	13	18	24	16	Netherlands	19.5	23	25	16
Russian Federation	16	36	46	49	Russian Federation	35.5	54.5	53	44.5
Singapore	-8	-26.5	-36.5	-50.5	Singapore	-10.5	-29.5	-43.5	-61
Spain	204	236	226	215	Spain	224	258	241	234
Sweden	2.5	-1	-4	-13.5	Sweden	1	-2	-6	-16
Switzerland	4	-2	-8	-14	Switzerland	4.5	-2.5	-7	-12
United Kingdom	2	-2	-9	-16	United Kingdom	1	-2	-6	-15
United States	-4	-6	-5	-4	United States	-4	-6.5	-8	-7

Note: Country median differentials calculated as the median for a country w of the difference between the CDS price for an issuer l that belongs to country w and the risk premium estimated with equation (2.37).

2.4 Transversal data analysis

Are the results of presented models in the above section very different among them when applied to CDS markets?

In this section, we start to answer this key question presenting some ad hoc results given by the different models that we introduced in the above section in order to better understand the possible differences due to the assumptions. We select the following dates: 30 January 2007, 30 January 2008, 30 January 2009, 29 January 2010, 31 January 2011, and 30 January 2012. Again, we use the 5-year CDS for senior unsecured debt, and we select different subsamples because of the interest of these particular classes. Finally, we use the next statistical models:

Lin_OLS = Linear ordinary least-squares regression.

Exp_OLS = Exponential ordinary least-squares regression.

Lin_MedReg = Linear median regression.

Exp_MedReg = Exponential median regression.

Med_3LHM = Median three-level hierarchical regression.

Av_3LHM = Mean three-level hierarchical regression.

In Table 2.11, we present the results for our first analysed subsample, AA North American financial sector. It is interesting to observe that the number of issuers with rating AA in the North American financial sector has been reduced from 44 to 18 because during the last crisis rating agencies began downgrading the ratings of financial issuers, especially from 2009 onwards. In addition, we see that in relative terms there has been a nearly 10-fold increase in these issuers compared to the initial spread levels in 2007, although the 2007 spread levels were very low. On the other hand, analysing the results of the different statistical models, the Lin_OLS estimates highlight that these results are not so similar to the rest of the models estimates, not even with the main statistics of the sample. The rest of the models produced similar estimates; however, the Lin_MedReg estimates are higher than the outcomes obtained by using an exponential model. This makes sense because the exponential models typically have a smoother effect than the linear models. Med_3LHM estimates and Av_3LHM estimates by definition are the same as the sample median and mean, respectively.

Table 2.11: AA North American financial sector. Main statistics (basis points)

Date	Nº Obs	Min	1Q	Median	Mean	3Q	Max	Lin_OLS	Exp_OLS	Lin_MedReg	Exp_MedReg	Med_3LHM	Av_3LHM
30/1/07	44	6.0	9.2	11.6	13.2	15.5	37.2	6.1	9.5	11.5	9.5	11.6	13.2
30/1/08	43	15.1	37.0	59.0	70.4	76.4	296.7	124.3	59.1	69.6	62.6	59.0	70.4
30/1/09	35	24.2	100.0	131.6	353.6	160.1	3187.0	371.4	151.0	182.6	139.5	131.6	353.6
29/1/10	28	34.6	62.0	87.2	140.8	148.2	680.5	187.3	91.1	99.7	82.4	87.2	140.8
31/1/11	26	38.9	76.7	93.4	150.3	129.3	800.9	144.8	97.2	105.9	91.1	93.4	150.3
30/1/12	18	27.9	80.7	115.1	182.5	195.6	943.1	160.2	111.4	119.9	100.9	115.1	182.5

Note: Lin_OLS = Linear ordinary least-squares regression estimate; Exp_OLS = Exponential ordinary least-squares regression estimate; Lin_MedReg = Linear median regression estimate; Exp_MedReg = Exponential median regression estimate; Med_3LHM = Median three-level hierarchical regression estimate; Av_3LHM = Mean three-level hierarchical regression estimate.

Table 2.12: A European financial sector. Main statistics (basis points)

Date	Nº Obs	Min	1Q	Median	Mean	3Q	Max	Lin_OLS	Exp_OLS	Lin_MedReg	Exp_MedReg	Med_3LHM	Av_3LHM
30/1/07	92	6.2	9.8	13.2	16.1	19.8	46.9	28.3	17.4	15.6	16.5	13.2	16.1
30/1/08	99	11.0	61.4	83.6	107.2	106.1	875.4	133.2	89.2	84.5	89.1	83.6	107.2
30/1/09	95	44.0	119.7	157.7	245.9	293.6	1506.0	449.6	241.8	226.0	218.8	157.7	245.9
29/1/10	97	45.5	94.1	119.4	145.6	180.1	462.8	204.7	121.9	120.2	118.8	119.4	145.6
31/1/11	86	49.6	107.0	171.1	219.2	218.0	1618.0	192.0	144.0	133.2	129.8	171.1	219.2
30/1/12	89	47.4	160.0	214.7	241.3	264.0	1282.0	276.6	192.1	185.1	179.8	214.7	241.3

Note: Lin_OLS = Linear ordinary least-squares regression estimate; Exp_OLS = Exponential ordinary least-squares regression estimate; Lin_MedReg = Linear median regression estimate; Exp_MedReg = Exponential median regression estimate; Med_3LHM = Median three-level hierarchical regression estimate; Av_3LHM = Mean three-level hierarchical regression estimate.

In the next example, we analyse the A financial sector in Europe (Table 2.12) to look at the effect of the financial crisis in Europe. The conclusions are similar to the previous ones with some nuances. First, we see that the number of issuers is relatively stable through the sample. A possible explanation for this is that the original 2007 A issuers were probably downgraded to BBB issuers, but at the same time some AAA and AA issuers were downgraded to A issuers, keeping the number of A issuers relatively stable over time. In terms of the main statistics, we see the same trend as in the case described above. This means a 16-fold increase in the A European financial spreads, from 13.2 to 215 basis points (b.p.) in terms of the median. Finally, we can appreciate that the financial crisis in Europe was more prolonged than in the US. In terms of the models estimates, we observe again that the Lin_OLS estimates are very inaccurate. On the other hand, Lin_MedReg, Exp_OLS and Exp_MedReg estimates provide very similar outcomes among them. It can be seen that these results are far from the original main statistics. The reason is that these models estimates use all of the available information for the A rating, all the information for the financial sector and all of the information for the European issuers (not just the information provided by the A European financial sector). Thus, if the analysed subsample is far from the rest of the sample in terms of the spread, then the results are too inaccurate, as in this example.

In the next analysis, we present the results of the BBB telecommunication services in Europe to see how the last crisis affected the corporate sector (Table 2.13). We observe that the number of issuers is relative stable over time, and probably the number of telecoms downgrades is much lower than in the financial sector. Similarly, we observe that the spread increased from 35.5 to 122.9 basis points, although in relative terms there was a 4-fold increase; therefore, the increase was much less than in the financial sector. It can even be observed that the BBB telecommunication services spread in 2012 was lower than the A financial spread, verifying that the crisis was mainly a financial crisis. In terms of the estimates, it can be observed that the Lin_OLS estimates are again very inaccurate, and we see that the Lin_MedReg, and Exp_MedReg outcomes are very similar, possibly describing the robustness of the median. However, Exp_OLS estimates are higher, as these results could be conditioned by the presence of outliers. It is thus clear that the Exp_OLS model estimate higher values than median regression models in this context. Finally, Med_3LHM estimates, and Av_3LHM estimates are the same as the median and the mean, respectively.

In the last case, we select the BB Latin American government (Table 2.14) for several reasons. The first is to select a sector with few observations in order to analyse the model performances under this circumstance. The next reason is that we are interested in studying the government spread behaviour during the crisis, and finally, due to the great increase in the GDP in the Latin American region. Our first observation is that in the case of Latin America, the information is less in terms of the number of issuers compared to Europe, Asia or North America and possibly with less data quality. First, we see that the number of issuers has decreased from eight to five, reflecting that there were perhaps several rating upgrades in the region in contrast to Europe or North America. In terms of the spread, we observe that the crisis has affected Latin America less than other regions (2.6 times higher), the spread increasing to 214 b.p. from original 80. As we said before, due to the rating upgrades, some BB issuers became BBB issuers; therefore, the factor of 2.6 could be even less if we use a fixed sample. In terms of the analysed models, it is interesting to highlight that the OLS models and median regression models are too far from the main statistics of the sample. This means that when the sample has few observations, these models do not fit so precisely. Furthermore, the spreads trend of this sample makes adjusting of these models very difficult. We have selected a sectorial subsample of the BB rating issuers that is an outlier among the all BB rating issuers, because of the particular economic conditions given in Latin America during the crisis. The GDP increase in this region during 2006-2012 favoured a relatively stable level of the credit spread in contrast to the rest of the regions.

To sum up, we could conclude that the different estimates depend on the used models. As they present considerable differences, it will be interesting to examine the performance of these models though time in order to extract conclusions about which could be the best approach in estimating credit curves.

Table 2.13: BBB European telecommunication services sector. Main statistics (basis points)

Date	Nº Obs	Min	1Q	Median	Mean	3Q	Max	Lin_OLS	Exp_OLS	Lin_MedReg	Exp_MedReg	Med_3LHM	Av_3LHM
30/1/07	16	21.1	27.3	35.5	46.3	56.9	112.1	48.1	39.5	40.9	42.5	35.5	46.3
30/1/08	16	42.3	69.5	74.1	76.2	89.2	102.3	82.8	89.6	90.6	88.4	74.1	76.2
30/1/09	18	74.6	105.2	141.3	158.5	166.5	387.9	127.3	185.1	165.6	165.6	141.3	158.5
29/1/10	16	32.1	65.9	91.5	88.0	112.3	146.0	121.8	92.4	91.2	92.0	91.5	88.0
31/1/11	18	35.4	70.5	82.0	118.5	133.7	382.1	98.5	99.8	96.4	96.6	82.0	118.5
30/1/12	15	43.4	87.0	122.9	206.5	171.9	1016.0	217.0	145.2	131.6	131.1	122.9	206.5

Note: Lin_OLS = Linear ordinary least-squares regression estimate; Exp_OLS = Exponential ordinary least-squares regression estimate; Lin_MedReg = Linear median regression estimate; Exp_MedReg = Exponential median regression estimate; Med_3LHM = Median three-level hierarchical regression estimate; Av_3LHM = Mean three-level hierarchical regression estimate.

Table 2.14: BB Latin American government sector. Main statistics (basis points)

Date	Nº Obs	Min	1Q	Median	Mean	3Q	Max	Lin_OLS	Exp_OLS	Lin_MedReg	Exp_MedReg	Med_3LHM	Av_3LHM
30/1/07	8	63.6	73.6	80.2	83.6	92.8	110.8	131.6	106.5	126.0	113.8	80.2	83.6
30/1/08	8	128.3	139.4	171.4	160.7	176.1	188.4	216.0	196.5	211.2	197.1	171.4	160.7
30/1/09	9	312.1	336.0	359.4	387.6	447.8	523.0	573.7	576.5	592.1	718.2	359.4	387.6
29/1/10	7	150.4	170.8	184.0	209.6	250.7	289.4	246.9	309.5	289.4	350.6	184.0	209.6
31/1/11	5	120.0	163.4	169.8	186.2	171.8	305.9	319.8	326.7	270.2	351.3	169.8	186.2
30/1/12	5	202.4	204.7	214.0	273.6	305.2	441.9	478.0	431.6	361.4	422.3	214.0	273.6

Note: Lin_OLS = Linear ordinary least-squares regression estimate; Exp_OLS = Exponential ordinary least-squares regression estimate; Lin_MedReg = Linear median regression estimate; Exp_MedReg = Exponential median regression estimate; Med_3LHM = Median three-level hierarchical regression estimate; Av_3LHM = Mean three-level hierarchical regression estimate.

2.5 Testing credit econometric models

2.5.1 Introduction

What econometric model of credit spread had the best performance during the crisis? How big are these differences? Are the differences among these models stable through the time? Does the rank order of the performance of these models depend on the sample criteria? What sample criterion is the best? In this section, we will answer these and other interesting questions by examining the behaviour of the credit spread econometric models during the period 2006-2012 on a daily basis.[4]

This section is divided into several parts: First we show the used sample criteria for this study. Next we will detail the used econometric models. Then we present the selected criteria for examining the models performance. Finally we show the results and conclusions.

2.5.2 Sample criteria

As we introduced in Subsection 1.8 in the first chapter, it is clear that the data quality influences the credit spread estimates. Thus, the question that arises is whether or not the order of the performance credit econometric model is conditioned by the used criteria sample. Furthermore, what would the most adequate sample criteria be? To answer these questions, we employ three different criteria, trying to cover a wide spectrum of possibilities.

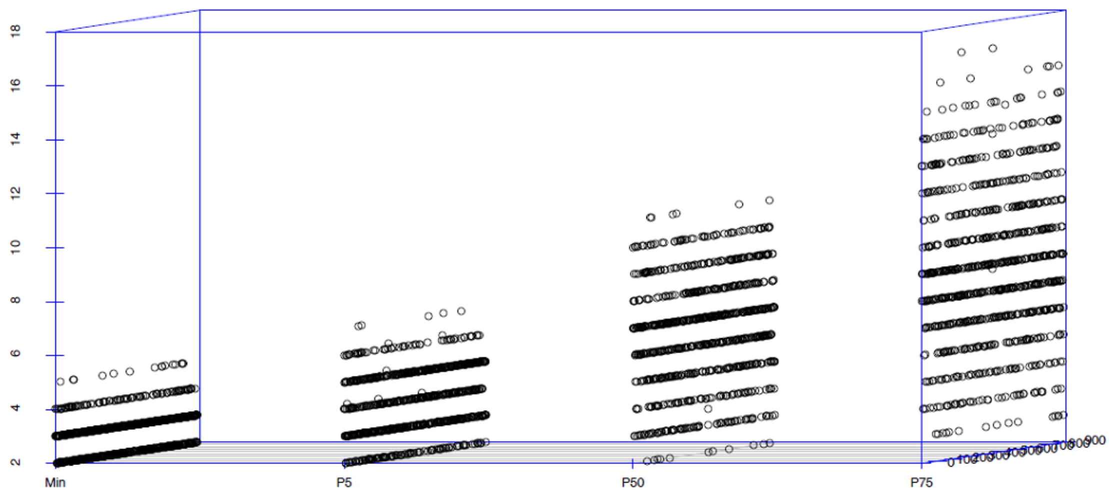
1. The first criteria ("non-filter") that we have selected is not to use any filter. This means that by using it we employ all the available price information in the CDS market, independently of the data quality rating of the CDS contract, or whatever other filter is used in that sense. Employing this criteria, the sample would be composed by approximately 1,500 issuers with a 5-year CDS for senior unsecured debt.

2. The second criteria ("BB Markit Rating") is based on the Markit data quality rating. As we introduced in Subsection 1.8, Markit states that particular confidence can be placed in BBB or higher ratings. At the same time, we are interested in getting the maximum available information in the credit market. Thus, we allow that the data quality rating to be one grade below a BBB. Therefore, the second criteria uses all the 5-year CDS contracts with a minimum data quality rating of BB on a daily basis. This means that the study sample changes daily. Once the sample is defined, all the CDS prices are weighted equally. Using this criteria, the sample would be composed by approximately 1,200 issuers with a 5-year CDS for senior unsecured debt.

3. Finally, we use a third criteria ("fixed sample") that is stricter than the previous ones. We propose the use of a fixed sample with the most liquid issuers. As an alternative to the Markit data quality rating criteria, we work with the number of pricing contributors to the 5-year CDS contract (CompositeDepth5y). For

[4]For this exercise we follow Faraway (2002) and Faraway (2005), and we use the next R packages Koenker (2012) and Genz and Bretz (2014).

Figure 2.9: Business day percentiles from 2006-2012 of the number of contributors of pricing to the 5-year CDS contract for each issuer



Note: X-axis: Business day percentiles. Y-axis: Number of contributors of pricing to the 5-year CDS contract. Z-axis: issuers. Therefore the P5% represents the number of contributors giving 5-year CDS prices for each issuer in the business day that was exactly the one with 5% fewer contributors to the 5-year CDS contracts for the period 2006-2012.

this reason, and after exploring several alternatives, we have opted for the following criteria. We select all the issuers that have had at least three contributors to their 5-year CDS contract for the 95% of the business days from 2006 to 2012. With this criteria, we use a fixed sample of 784 issuers. Figure 2.9 shows the different percentiles of the number of pricing contributors to the 5-year CDS for each issuer during the business days between 2006 and 2012. This means that, for example, P5% represents the number of contributors giving 5-year CDS prices for each issuer in the business day, which was exactly the one with 5% fewer contributors to the 5-year contracts for the period 2006-2012. From this chart we can also see evidence of the lack in liquidity of the CDS market due to the small number of contributors giving prices.

2.5.3 Analysed models

For this analysis we have used the statistical models presented in Subsection 2.4:

Lin_OLS = Linear ordinary least-squares regression.

Exp_OLS = Exponential ordinary least-squares regression.

Lin_MedReg = Linear median regression.

Exp_MedReg = Exponential median regression.

Med_3LHM = Median three-level hierarchical regression.

Av_3LHM = Mean three-level hierarchical regression.

In addition, we have used other alternatives for the three-level hierarchical regression were CDS lacks of data in any combination of rating, sector and region. These are the alternatives:

Rat_Med_1LHR = Median one-level hierarchical regression, using the rating as explanatory variable, applying equation (2.30).

Rat_Av_1LHR = Mean one-level hierarchical regression, using the rating as explanatory variable, applying equation (2.30).

RatSec_Med_2LHR = Median two-level hierarchical regression, using the rating and sector as explanatory variables applying equation (2.34).

RatSec_Av_2LHR = Mean Two-Level Hierarchical Regression, using the rating and sector as explanatory variables applying equation (2.34).

RatGeo_Med_2LHR = Median two-level hierarchical regression, using the rating and region as explanatory variables applying equation (2.37).

RatGeo_Av_2LHR = Mean two-level hierarchical regression, using the rating and region as explanatory variables applying equation (2.37).

RatSec_Med_2LHR_Reg = Median two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a median % differential region factor to adjust the credit spread as in equation (2.53).

RatSec_Av_2LHR_Reg = Mean two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a mean % differential region factor to adjust the credit spread as in equation (2.53) .

RatSec_Med_2LHR_RegRat = Median two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a median % differential region-rating factor to adjust the credit spread as in equation (2.50).

RatSec_Av_2LHR_RegRat = Mean two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a mean % differential region-rating factor to adjust the credit spread as in equation (2.50).

RatSec_Med_2LHR_Cty = Median two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a median % differential country factor to adjust the credit spread as in equation (2.54).

RatSec_Av_2LHR_Cty = Mean two-level hierarchical regression, using the rating and sector as explanatory variables firstly, and then adding a mean % differential country factor to adjust the credit spread as in equation (2.54).

2.5.4 Criteria for the selection of the best approach

What criteria should we use in order to determine the best statistical model presented above? In this section, we detail three criteria that should be taken into account in order to know what the best model is.

1. The first criteria, without any doubt, has to be a measure of how good the estimates fit in the original dataset. Consequently, we employ the sum of the absolute errors for each day to analyse the performance of the presented models in Subsection 2.5.3. We work with the sum of the absolute errors instead the sum of the quadratic errors to avoid overweighting the possible outliers of the sample.
2. The second criteria is based on the volatility estimates. As we mentioned in the introduction, financial institutions generally desire little volatility in the credit spread series for managing their risk. This means that sometimes we can reduce the estimates accuracy if we reduce the volatility of these estimated series.
3. Finally, we look at the implementation and maintenance of these models on financial institutions. Following the results, we explain briefly if there is any significant difference in terms of time and costs for a financial institution in using the different models to decide to use a particular model instead of another one.

2.5.5 Applied methodology

After presenting the different filters used for the dataset (Subsection 2.5.2), the models used (Subsection 2.5.3) and the criteria to examine the results (Subsection 2.5.4), we will then detail the applied methodology.

Firstly, for this study, we use the daily senior 5-year CDS contract with the standard currency and restructuring clause for each issuer of the sample. We use this particular criterion because of its liquidity and representativeness. (For more detail see Subsection 2.5.4). The analysed period is from 2006 to 2012, as we think that it is the most relevant period of time for the credit market.

Secondly, we estimate all the presented models to determine the sum of the absolute error. This means that we calculate the absolute difference between the estimated risk premium and the real price, and then we add all these errors of the issuers included in the sample. We suppose that the exposure of each issuer is the same and equals to one unit.

Finally, we estimate the spread for each class grouped by rating, industry and region. Then we estimate the volatility of each class included in the sample with a one year data window, and we average the different estimated volatility for each class to get the estimated volatility of the model for each day. We highlight that to estimate the volatility, we only use the classes (combinations of rating, sector, and region) that are presented in the sample during everyday of the analysed period. This means that for example, if we do not have data on the BB Oceania basic material sector for a particular day, such estimate spread series would not be included in the sample of this study to average the volatility of the model. Therefore, we have a sample of 186 classes for the "non-filter" sample, 120 classes for the BB Markit sample, and 107 for the "fixed sample".

2.5.6 Results

2.5.6.1 Rating-sector-region class spread estimates

Firstly, we show the estimates for the A financial sector in Europe, North America, and Asia using the different models and using the “BB Markit sample” in Figures 2.10, 2.11 and 2.12, respectively. In this case, we observe that some days, in the presence of high market volatility, the differences among the spread estimates by the presented models are very considerable. Furthermore, the financial sector distribution is right-skewed by the financial crisis, resulting in a big difference between the estimates based on the median and those based on the mean. Finally, we present the BBB basic material in North America and Europe, using the BB Markit sample in Figures 2.13 and 2.14. Again, we observe a significant difference depending on the models used. Especially, significant is the difference in the analysed period of time between the model based on the median and that based on the mean.

Figure 2.10: A European financial sector spread estimates using different models with BB Markit sample. 2006-2012

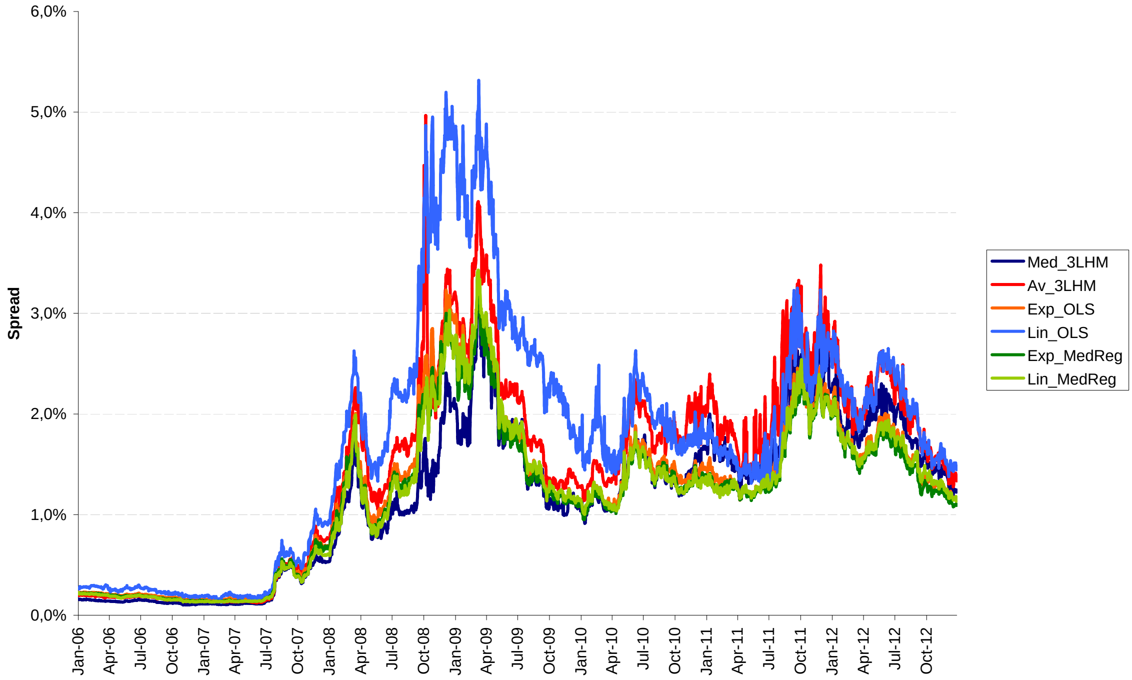


Figure 2.11: A North American financial sector spread estimates using different models with BB Markit sample. 2006-2012

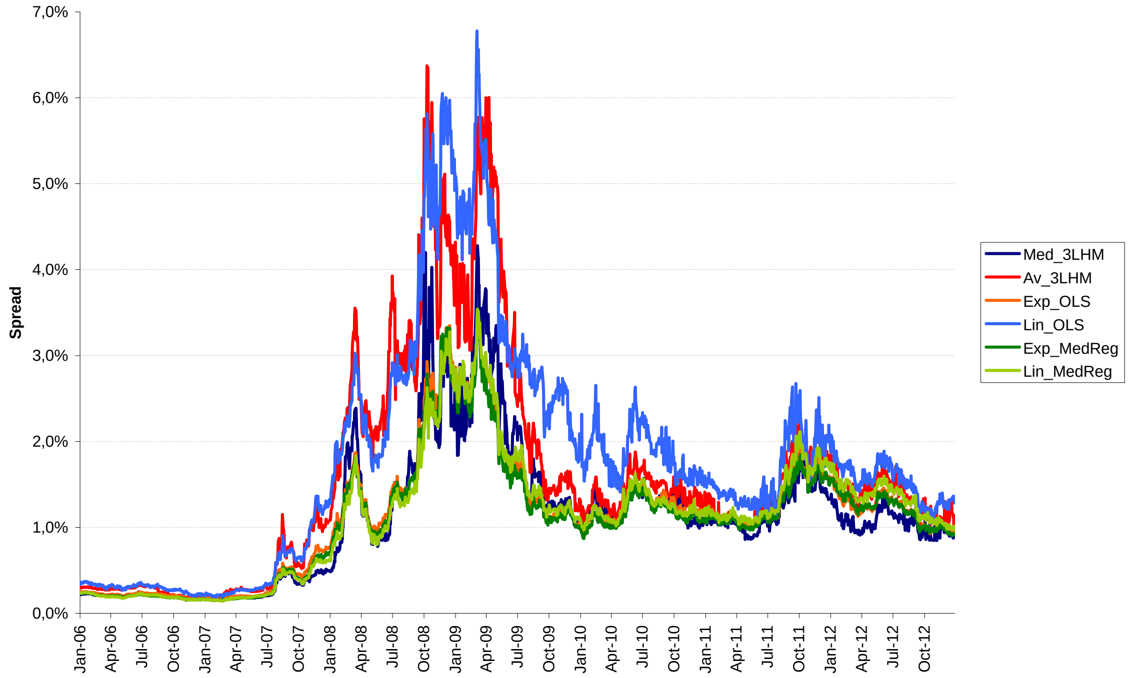


Figure 2.12: A Asian financial sector spread estimates using different models with BB Markit sample. 2006-2012

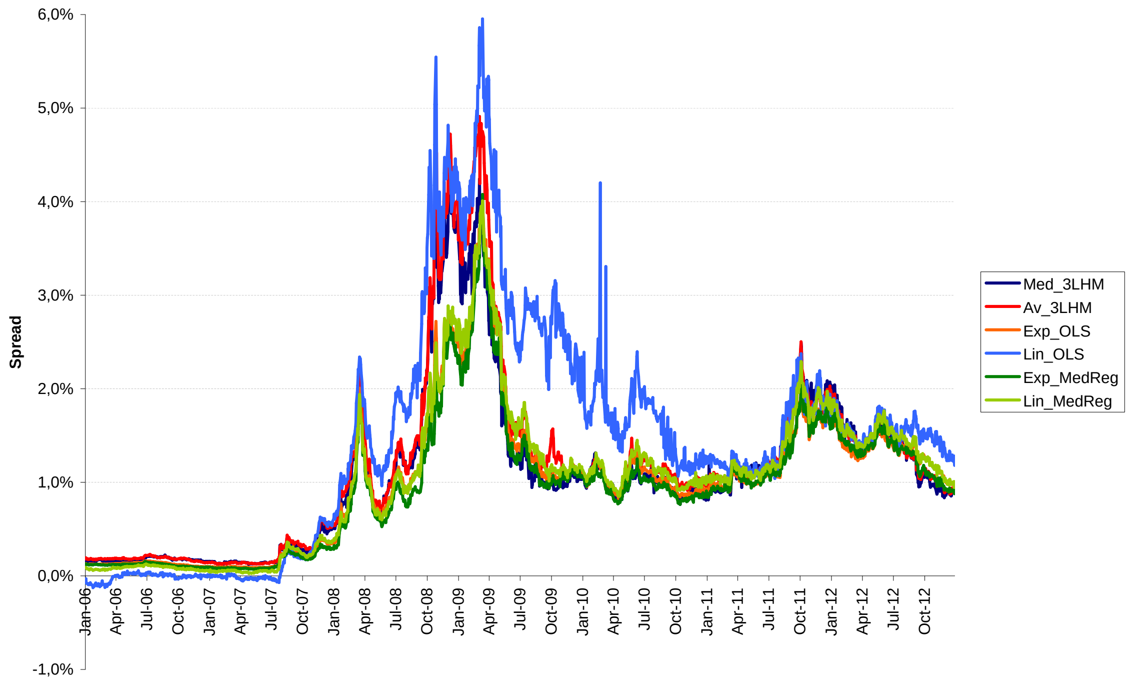


Figure 2.13: BBB European basic materials sector spread estimates using different models with BB Markit sample. 2006-2012

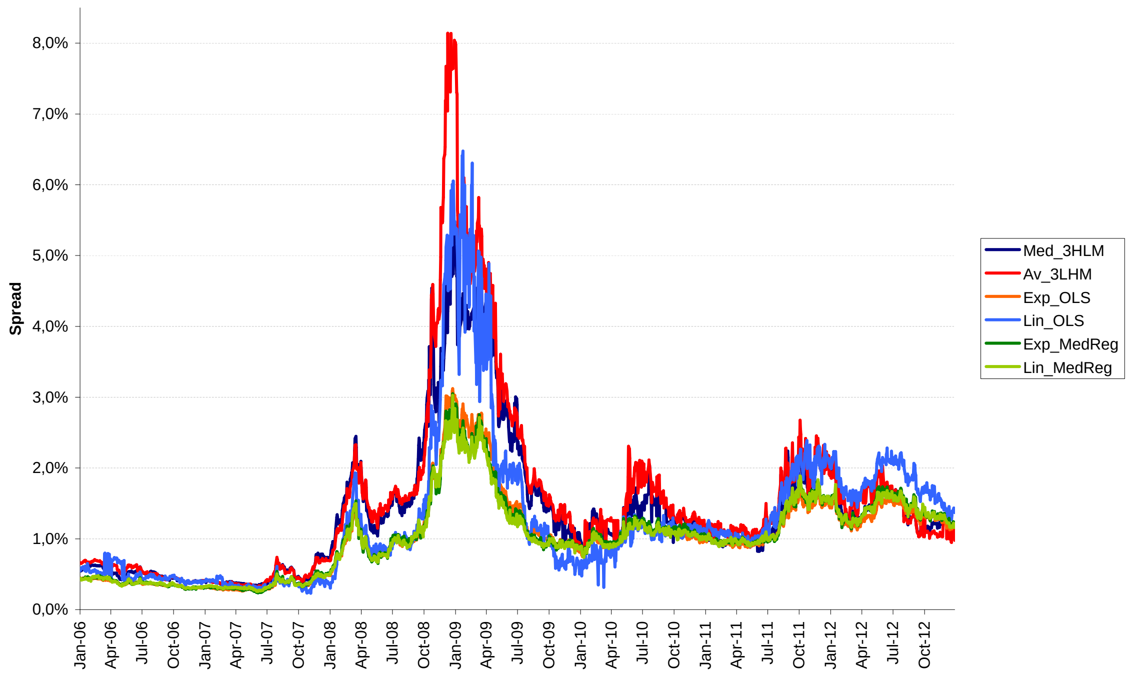
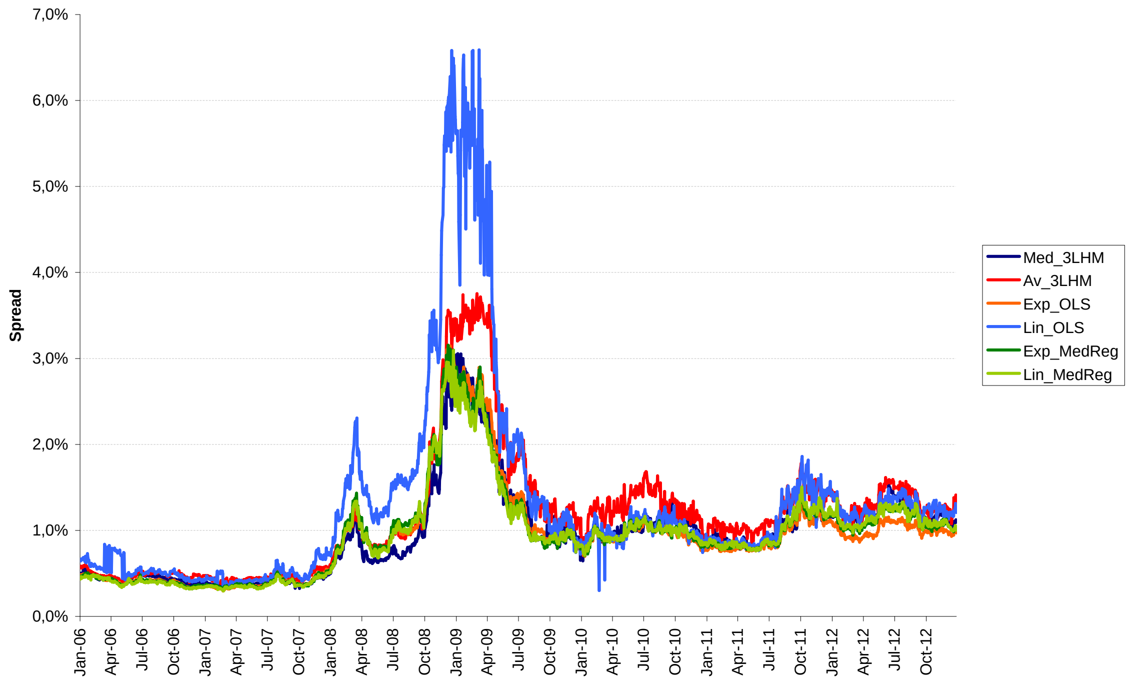


Figure 2.14: BBB North American basic materials sector spread estimates using different models with BB Markit sample. 2006-2012



2.5.6.2 Daily models' performance from 2006 to 2012

In this last section, we show the results of all the models presented in Subsection 2.5.3 in terms of the sum of the absolute errors and the series volatility with the different sample criteria according to Subsection 2.5.2. Given that the analysed period is so long, we decided to present the results distinguishing three periods of time. Thus, we consider that a good division could be the next one: Pre-crisis period (2006-2007) , crisis period, (2008-2010) and post-crisis period (2011-2012), although is very difficult to establish an exact line that separates the different periods.

Table 2.15: “Non-Filter” sample results. 2006-2007

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	9.23	10.39	11.89	14.08	11.84	11.86	12.30	13.46
% Respect to Min.	100%	113%	129%	153%	128%	128%	133%	146%
Average Vol.	73.2%	75.1%	30.6%	502.2%	52.2%	105.3%	27.1%	28.4%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	11.30	12.66	11.12	12.47	11.13	12.57
% Respect to Min.	122%	137%	120%	135%	121%	136%
Average Vol.	55.2%	51.2%	43.5%	44.9%	64.0%	61.4%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	10.66	12.85	10.63	12.56
% Respect to Min.	116%	139%	115%	136%
Average Vol.	68.5%	70.6%	61.6%	61.3%

Pre-crisis period

Table 2.16: "BB Markit" sample results. 2006-2007

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	4.96	5.47	6.46	7.61	6.39	6.51	6.78	7.30
% Respect to Min.	100%	110%	130%	153%	129%	131%	137%	147%
Average Vol.	80.1%	72.7%	38.8%	537.9%	58.7%	153.0%	31.5%	29.9%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	6.21	6.74	6.09	6.68	6.08	6.52
% Respect to Min.	125%	136%	123%	135%	123%	131%
Average Vol.	71.6%	56.3%	51.9%	45.5%	79.0%	65.1%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	5.75	6.77	5.73	6.56
% Respect to Min.	116%	136%	115%	132%
Average Vol.	82.8%	73.0%	75.5%	68.6%

Table 2.17: "Fixed sample" results. 2006-2007

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	2.75	3.11	3.87	4.92	3.84	3.86	4.00	4.45
% Respect to Min.	100%	113%	141%	179%	140%	140%	145%	162%
Average Vol.	84.8%	78.4%	43.6%	924.9%	79.9%	205.9%	35.6%	38.2%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	3.54	4.06	3.59	4.14	3.51	4.02
% Respect to Min.	129%	148%	131%	150%	128%	146%
Average Vol.	76.9%	63.6%	59.6%	51.6%	85.8%	73.6%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	3.36	3.98	3.30	3.87
% Respect to Min.	122%	145%	120%	141%
Average Vol.	90.6%	82.9%	83.8%	77.7%

Table 2.18: “Non-Filter” sample results. 2008-2010

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	38.46	44.25	47.15	57.76	47.06	47.33	50.47	57.24
% Respect to Min.	100%	115%	123%	150%	122%	123%	131%	149%
Average Vol.	83.7%	82.8%	41.2%	773.1%	60.8%	112.5%	39.2%	43.0%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	46.02	52.34	46.24	53.01	45.37	52.21
% Respect to Min.	120%	136%	120%	138%	118%	136%
Average Vol.	67.4%	61.1%	60.1%	62.3%	75.9%	71.8%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	43.59	51.85	44.14	52.32
% Respect to Min.	113%	135%	115%	136%
Average Vol.	81.4%	81.2%	77.7%	75.1%

Crisis period

Table 2.19: “BB Markit” sample results. 2008-2010

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	18.53	20.50	23.47	27.05	23.36	23.39	25.07	27.43
% Respect to Min.	100%	111%	127%	146%	126%	126%	135%	148%
Average Vol.	122.7%	107.8%	59.3%	838.4%	76.4%	172.8%	52.1%	56.8%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	22.16	24.26	23.06	25.50	21.83	23.98
% Respect to Min.	120%	131%	124%	138%	118%	129%
Average Vol.	101.9%	92.0%	83.7%	77.9%	110.1%	101.6%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	20.99	23.87	20.90	23.76
% Respect to Min.	113%	129%	113%	128%
Average Vol.	119.1%	114.2%	107.6%	102.8%

Table 2.20: “Fixed Sample” results. 2008-2010

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	9.88	11.22	14.58	18.20	14.51	14.69	15.75	17.74
% Respect to Min.	100%	114%	148%	184%	147%	149%	159%	180%
Average Vol.	100.3%	88.4%	50.1%	906.7%	91.8%	237.7%	50.7%	53.1%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	13.16	14.96	13.90	15.94	12.97	14.92
% Respect to Min.	133%	151%	141%	161%	131%	151%
Average Vol.	90.2%	71.3%	73.8%	69.5%	97.4%	80.4%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	12.18	14.54	12.47	14.91
% Respect to Min.	123%	147%	126%	151%
Average Vol.	104.9%	94.1%	98.2%	87.2%

Table 2.21: “Non-Filter” sample results. 2011-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	26.04	23.34	30.80	34.21	30.73	30.09	32.81	35.73
% Respect to Min.	100%	90%	118%	131%	118%	116%	126%	137%
Average Vol.	65.9%	63.4%	28.6%	486.8%	42.8%	46.2%	27.4%	33.1%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	29.37	32.51	29.59	32.41	28.96	32.30
% Respect to Min.	113%	125%	114%	124%	111%	124%
Average Vol.	46.7%	50.2%	41.7%	46.3%	53.9%	58.9%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	27.94	32.23	27.44	31.80
% Respect to Min.	107%	124%	105%	122%
Average Vol.	58.7%	65.8%	55.2%	58.8%

Post-crisis period

Table 2.22: “BB Markit” sample results. 2011-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	9.21	10.02	12.32	13.56	12.24	11.90	13.15	14.09
% Respect to Min.	100%	109%	134%	147%	133%	129%	143%	153%
Average Vol.	122.7%	113.8%	52.6%	533.1%	67.4%	73.9%	42.7%	60.3%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	11.38	12.44	11.66	12.43	11.24	12.26
% Respect to Min.	124%	135%	127%	135%	122%	133%
Average Vol.	92.1%	98.6%	72.3%	78.6%	99.4%	106.1%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	10.41	14.24	10.18	11.68
% Respect to Min.	113%	155%	110%	127%
Average Vol.	109.4%	118.5%	92.0%	100.3%

Table 2.23: “Fixed sample” results. 2011-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Sum Abs. Errors	7.22	8.10	11.00	12.76	10.93	10.73	11.67	12.82
% Respect to Min.	100%	112%	153%	177%	151%	149%	162%	178%
Average Vol.	71.9%	64.0%	36.7%	559.5%	70.1%	78.5%	38.3%	42.5%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Sum Abs. Errors	9.84	11.19	10.48	11.60	9.74	11.23
% Respect to Min.	136%	155%	145%	161%	135%	156%
Average Vol.	64.1%	55.7%	64.8%	54.6%	71.4%	64.6%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	9.05	11.82	9.18	11.37
% Respect to Min.	125%	164%	127%	158%
Average Vol.	79.5%	76.0%	71.8%	68.8%

Table 2.24: "BB Markit" sample results. 2006-2012

Models 2.5.3	*Med_3LHM*	*Exp_Av_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*
Sum Abs. Errors	12.00	12.55	13.22	15.44	17.66	15.35	15.30
% Respect to Min.	100%	105%	110%	129%	147%	128%	127%
Average Vol.	115.6%	94.9%	104.0%	53.6%	687.0%	70.5%	136.6%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*
Sum Abs. Errors	14.54	15.89	14.96
% Respect to Min.	121%	132%	125%
Average Vol.	93.6%	88.2%	74.6%

Models 2.5.3	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*	*RatSec_Med_2LHR_RegRat*
Sum Abs. Errors	16.40	14.32	15.65	13.62
% Respect to Min.	137%	119%	130%	114%
Average Vol.	72.7%	101.4%	97.0%	109.8%

Models 2.5.3	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Sum Abs. Errors	16.24	13.51	15.41
% Respect to Min.	135%	113%	128%
Average Vol.	108.7%	97.1%	96.2%

2.5.6.3 Exponential mean three-level hierarchical regression

In this case, we show the results of using an exponential mean three-level hierarchical regression (*Exp_Av_3LHM*) to analyse if we reduce the volatility of the spread estimate series. We present the outcomes from 2006 to 2012, with the "BB Markit rating" criteria in Table 2.24. It can be observed that the exponential models generally produce lower volatility of the estimates.

2.5.6.4 Average ten-day spread estimates vs daily spreads estimates

In Figure 2.15, we show the average 10-day spread estimates for the AA European financial sector versus the daily AA European financial sector. It is clear that with this simple average we reduce the volatility of the estimates, which is desirable for the risk management of financial institutions.

2.5.6.5 Different samples for sector spread estimates

In Figure 2.16, we present the results for AA European financial spread estimates from 2006 to 2012, applying three different samples criteria. In general, as we also show in Subsection 2.5.6.2, the sample criteria is not so decisive except for a few days, as we saw in the year 2012 where the fixed sample AA European financial estimates had a different pattern compared to the other two samples (BB Markit rating and "Non-Filter").

Figure 2.15: Daily AA European financial sector estimate vs ten-day average AA Europe financial sector estimate with BB Markit sample. 2006-2012

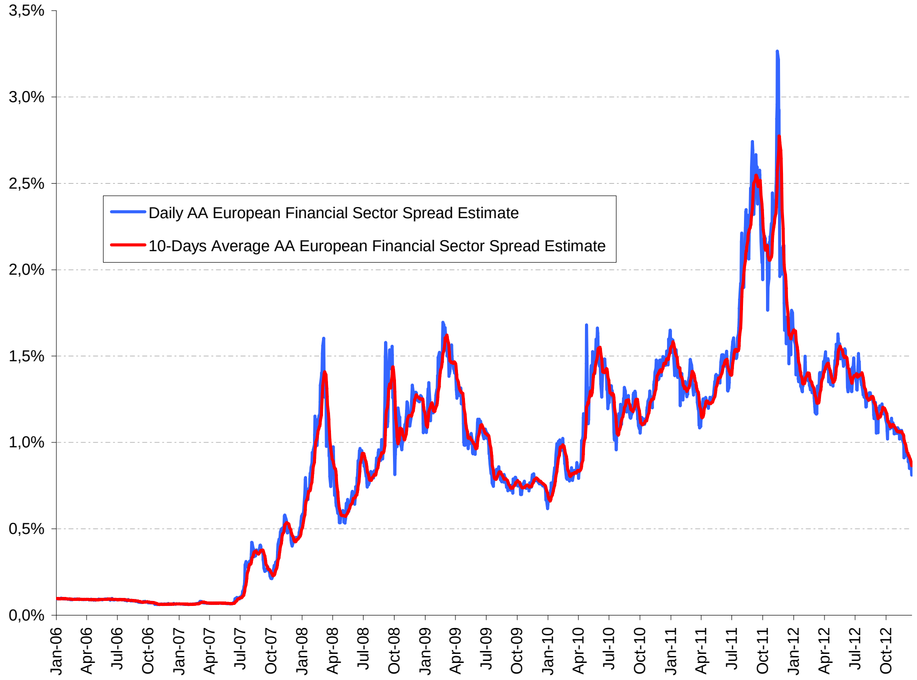
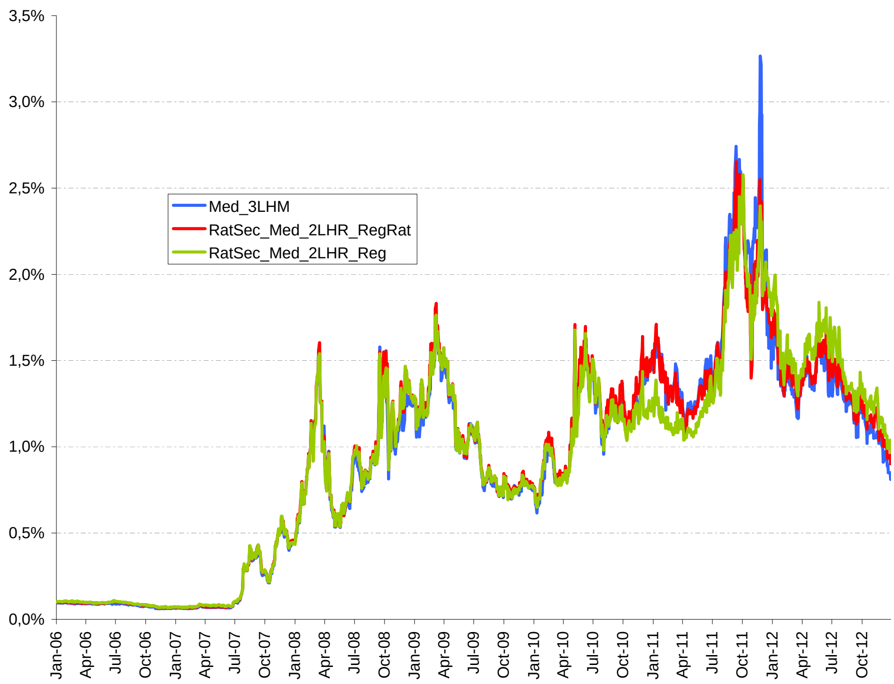


Figure 2.16: AA European financial spread estimates with different samples criteria. 2006-2012

Figure 2.17: AA European financial sector with BB Markit rating estimates under the best fit models. 2006-2012



2.5.6.6 Different samples for sector spread estimates

In Figure 2.17, we present the graph to present the AA European financial estimates with the "BB Markit rating" sample, using the median three-level hierarchical regression and two good alternatives in the cases where we do not have data such as the RatSec_Med_2LHR_Reg (2.5.3) and the RatSec_Med_2LHR_RegRat (2.5.3).

2.5.6.7 Quantifying model risk

In this last section, we calculate daily the difference between the sum of the absolute errors using the Med_3LHM (2.5.3) and the rest of the models divided by the sum of the absolute error of the Med_3LHM for the period 2006-2012. In Tables 2.25, 2.26 and 2.27, we show the results of the percentiles of that distribution for each model applying the criteria of the different samples. Either the 95th or the 99th percentile could be a good proxy of the model risk when we are interested in pricing credit financial assets without a market risk premium.

Table 2.25: "Non-Filter" sample results. 2006-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Minimum	0.00%	6.91%	2.13%	30.02%	2.11%	1.88%	2.57%	34.72%
75th Percentile	0.00%	14.05%	31.31%	56.62%	31.07%	29.73%	38.04%	52.43%
95th Percentile	0.00%	18.49%	38.13%	67.15%	37.67%	36.96%	46.66%	62.08%
99th Percentile	0.00%	23.27%	44.58%	82.12%	44.46%	42.52%	51.17%	69.75%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Minimum	1.70%	23.31%	1.69%	27.90%	1.59%	22.49%
75th Percentile	24.74%	40.71%	24.03%	39.41%	23.35%	40.07%
95th Percentile	30.87%	49.33%	32.72%	47.41%	29.01%	49.71%
99th Percentile	34.95%	62.15%	35.88%	61.29%	33.48%	66.10%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Minimum	1.27%	20.17%	1.16%	21.12%
75th Percentile	18.31%	40.59%	18.24%	39.46%
95th Percentile	24.47%	57.05%	22.54%	50.05%
99th Percentile	29.45%	68.36%	27.50%	67.65%

Note: The results shows several percentiles of the distribution calculated as the daily difference between the sum of the absolute errors using the Med_3LHM (2.5.3) and the rest of the models divided by the sum of the absolute error of the Med_3LHM for the period 2006-2012.

Table 2.26: "BB Markit" sample results. 2006-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Minimum	0.00%	5.70%	18.35%	28.98%	18.49%	17.54%	23.89%	3.59%
75th Percentile	0.00%	11.08%	32.56%	53.37%	31.42%	31.73%	40.40%	52.73%
95th Percentile	0.00%	13.80%	47.72%	77.05%	46.85%	42.75%	57.46%	71.14%
99th Percentile	0.00%	16.37%	58.63%	110.79%	57.55%	53.02%	67.26%	91.22%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Minimum	11.91%	23.26%	16.10%	27.40%	11.64%	20.70%
75th Percentile	25.22%	36.14%	26.75%	37.77%	22.94%	32.89%
95th Percentile	35.51%	51.83%	30.82%	42.04%	33.88%	49.45%
99th Percentile	45.06%	68.22%	33.52%	46.79%	43.16%	64.57%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Minimum	7.93%	17.01%	0.09%	12.59%
75th Percentile	15.28%	35.27%	15.71%	32.23%
95th Percentile	18.77%	90.28%	22.91%	46.14%
99th Percentile	22.70%	291.15%	30.50%	64.31%

Note: The results shows several percentiles of the distribution calculated as the daily difference between the sum of the absolute errors using the Med_3LHM (2.5.3) and the rest of the models divided by the sum of the absolute error of the Med_3LHM for the period 2006-2012.

Table 2.27: "Fixed sample" results. 2006-2012

Models 2.5.3	*Med_3LHM*	*Av_3LHM*	*Exp_OLS*	*Lin_OLS*	*Exp_MedReg*	*Lin_MedReg*	*Rat_Med_1LHR*	*Rat_Av_1LHR*
Minimum	0.00%	3.60%	17.80%	47.28%	16.39%	17.45%	18.49%	48.14%
75th Percentile	0.00%	11.93%	44.13%	73.90%	43.22%	44.14%	54.56%	71.93%
95th Percentile	0.00%	18.37%	77.16%	127.96%	75.93%	76.63%	86.39%	114.26%
99th Percentile	0.00%	20.99%	107.62%	235.97%	109.37%	108.99%	122.21%	167.78%

Models 2.5.3	*RatSec_Med_2LHR*	*RatSec_Av_2LHR*	*RatGeo_Med_2LHR*	*RatGeo_Av_2LHR*	*RatSec_Med_2LHR_Reg*	*RatSec_Av_2LHR_Reg*
Minimum	11.92%	22.32%	10.94%	37.35%	12.48%	21.86%
75th Percentile	31.30%	48.57%	38.06%	56.45%	29.42%	47.72%
95th Percentile	50.10%	72.33%	61.71%	87.38%	50.82%	73.81%
99th Percentile	84.45%	118.66%	95.91%	131.95%	92.04%	137.68%

Models 2.5.3	*RatSec_Med_2LHR_RegRat*	*RatSec_Av_2LHR_RegRat*	*RatSec_Med_2LHR_Cty*	*RatSec_Av_2LHR_Cty*
Minimum	9.75%	24.45%	7.77%	18.41%
75th Percentile	23.23%	45.20%	22.14%	44.98%
95th Percentile	36.24%	81.43%	50.25%	88.25%
99th Percentile	62.00%	111.60%	93.30%	145.53%

Note: The results shows several percentiles of the distribution calculated as the daily difference between the sum of the absolute errors using the Med_3LHM (2.5.3) and the rest of the models divided by the sum of the absolute error of the Med_3LHM for the period 2006-2012.

Table 2.28: Rating probability of default

Rating	PD
AAA	0.01%
AA+	0.02%
AA	0.03%
A+	0.05%
A	0.08%
A-	0.1%
BBB+	0.1367%
BBB	0.2019%
BBB-	0.3059%
BB+	0.5111%
BB+	1.00%
BB-	1.5001%
B+	2.5493%
B	4.4117%
B-	7.8513%
CCC	21.2175%
D	100.00%

2.5.7 How to deal with the "inversion problem"

As we presented in Subsection 1.4 in the first chapter, it is usual that the median spread of a particular rating class has a normal value compared to the rest of the ratings, meaning that higher quality ratings have lower spreads. However, under market stress conditions, we observe that in some cases this does not happen. These market stress conditions lead to higher quality ratings having wider spreads. Thus, how should we manage this problem in assigning a price for a new credit asset in our portfolio? We propose the following method:

In case the next order relation is not true for the market spread values: $AAA < AA < A < BBB < BB < B$[5], we correct the spread value in the market using the below expression (we assume the first initial "true" spread is the rating spread with the most market observations, and depending on the sector, this rating will typically be the A or the BBB rating).

A log-linear relationship between the CDS spread and the probability of default is assumed .

$$\begin{aligned} Ln(CDS_{rating2}) &= pLn(CDS_{rating1}) + (1-p)Ln(CDS_{rating3}) \\ PD_{rating2} &= pPD_{rating2} + (1-p)PD_{rating3} \qquad , rating3 < rating2 < rating1 \end{aligned} \tag{2.56}$$

Considering Table 2.28 for assigning a probability of default to the different ratings, we achieve the following outcomes for assigning the corrected spread values in Table 2.29. Of course, it is worth noting that these corrections can also be applied to a particular rating-sector class, or a specific rating-sector-region class.

[5]We normally exclude the CCC rating because we have very few observations, although we estimate the CCC value by extrapolation.

Table 2.29: Inverse spread proposed correction

Case	Correction
$AAA > AA$	$ln(AAA) = (3/2) \cdot (ln(AA) - ln(A)/3)$
$AA > A$	$ln(AA) = (1/0.71) \cdot (ln(A) - 0.29 \cdot ln(BBB))$
$A > BBB$	$ln(A) = (1/0.85) \cdot (ln(BBB) - 0.15 \cdot ln(BB))$
$BBB > BB$	$ln(BB) = 0.16 \cdot ln(B) + 0.84 \cdot ln(BBB)$
$BB > B$	$ln(B) = (1/0.16) \cdot (ln(BB) - 0.84 \cdot ln(BBB))$

2.6 Conclusions and open questions

In this second chapter, we have presented different econometric models to estimate sector credit curves. After an exhaustive analysis of the different model results, our main conclusions are the following:

It is thus clear that the model that best fits is Med_3LHM (2.5.3) in terms of the sum of absolute errors, followed by Av_3LHM (2.5.3). The hierarchical regression models generally fit much better than the non-hierarchical regression. In addition, the rank order of these models is not altered by the analysed period of time. This means that these models rank almost in the same order independently of the analysed time window. However, it is obvious that during the denominated “crisis” period, these errors are much higher than in the rest of the periods. In case of not being able to adjust a three-level hierarchical regression, given the lack of data, we find that RatSec_Med_2LHR_Reg (2.5.3), RatSec_Med_2LHR_RegRat (2.5.3), and RatSec_Med_2LHR_Cty (2.5.3) are good proxy alternatives [for an example, see Subsection 2.5.6.6]. It can also be observed that, as we expected, based on the economic theory, the RatSec_Med_2LHR (2.5.3) produces a better fit than the RatGeo_Med_2LHR (2.5.3), indicating that the sector is more relevant than the region as an explanatory risk variable in the corporate world. Analysing the results of the non-hierarchical models, we prefer Exp_OLS (2.5.3) because this model produces an outcome similar to Lin_MedReg (2.5.3) and Exp_MedReg, but with lower volatility. Undoubtedly, the worst model is Lin_OLS (2.5.3). Furthermore, in general, we prefer the median estimate to the mean estimate due to its robustness when assigning the price of an new credit asset without a credit spread, minimizing the “inversion problem” presented in Subsection 1.4 in the first chapter. Finally, the other fundamental reason for using the median is the right-skewed distribution of the CDS spread, also presented in Subsection 1.4.

It is worth mentioning that the estimation error as the difference between the sum of the absolute errors using Med_3LHM (2.5.3) and the rest of the models divided by the sum of the absolute error of Med_3LHM is much higher when we use the 95th or the 99th percentile instead of the average error for 2006-2012. This means that the pricing error of a portfolio could be very high during some specific days. However, the model rank is the same as in Subsection 2.5.6.2 (Daily Models Performance from 2006 to 2012), meaning that there are no order changes among the models when we use the error maximum instead of the average error of a particular mode, and also with independence of the sample criteria.

In terms of volatility, we have observed that the exponential models smooth the changes due to the rating, sector or regional factors, by estimating a less volatile series spread than the linear models. It is important to note that with respect to the sample criteria and related to series volatility, we observe that the estimates series are less volatile when we use the "non-filter" criteria. Our explanation for this is that the lowest quality rating data are less volatile than the rest of the data. This could be because the lower quality rating data always has the same value due to their illiquidity; therefore, if we include those data in the sample, we reduce the overall series volatility. In addition to this, related to the series volatility issue, we observe that if we use a 10-day period instead of just the data of the previous day to estimate credit curves, we avoid market noise. This is thus a much more adequate method of pricing credit financial assets in the banking book, such as loans or financial guarantees, as we use the credit market trend reducing the valuation volatility (see Subsection 2.5.6.4).

Regarding the sample criteria, we observe that all the results are rescaled in terms of the sum of the absolute errors and series volatility. This means that all of the econometric models presented in this chapter show the same trend independently of the selected sample. It is relevant because the selected sample criteria do not introduce additional model risk and because these criteria do not affect the model ranking. However, under some circumstances, the estimates series could be conditioned by the selected criteria as we showed in Subsection 2.5.6.5. We propose, therefore, the "BB Markit rating" as the best criteria because it allows us to use the quantitative and qualitative quality factor of the data, and at the same time, all the "good" price information available daily in the market, such as the sample changes to estimate credit curves.

Finally, it is also worth mentioning that, from an implementation point of view, all the presented models in this chapter should have a similar level of difficulty; and therefore, the different models have a similar implementation cost.

However, there are still some open questions to answer, as for example: What is the minimum number of observations for estimating a three-level hierarchical model instead of a two-level hierarchical model as RatSec_Med_2LHR_Reg (2.5.3), RatSec_Med_2LHR_RegRat (2.5.3)? On the other hand, what financial variables could anticipate possible fluctuations in the risk premium? Which sectors are the most volatile? How related are the different sectors? These last questions and other pertinent ones will be answered in the next chapter.

Chapter 3

Sectorial Asset Allocation

3.1 Introduction

Systemic risk can be defined as the possibility that the financial system as a whole might become unstable, as opposed to the failure of a single institution. The default of an individual entity could translate into a systemic risk crisis because its contractual and economic relationships with other economic agents might extend the shock to the rest of the economy, with dramatic effects in terms of GDP and unemployment. A firm with a large idiosyncratic component of risk could default with a minor impact on its sector, while the contrary will happen for a firm which is systemic in its sector. It is therefore important to estimate the relevance of each firm in a given sector, as well as the relevance of each sector in the global economy, which are the two goals of this paper. When applied to the financial sector, this is an especially relevant analysis that might help to identify the systemic financial institutions. The most widely used measures of systemic risk use information on CDS spreads, which are forward-looking and reflect the market perception of the credit risk of the issuer. Hence, we are interested in characterizing how the CDS spreads in different sectors relate to each other, as well as in how the CDS spreads of different firms operating in a given sector correlate among them.

We start by analysing the commonality of credit risk across all different sectors, regions and entities. That will provide us with a global risk factor that captures elements common to all sectors. The sensitivity of each sector to the global risk factor will inform us of how systemic each credit sector is and in which sectors risk has a more specific nature. We also want to characterize the determinants of the global risk factor, analysing which financial indicators contain more information on credit risk globally, as well as at the sectorial level. That will suggest to us how to estimate a factor model for credit risk. Such analysis should enable us to characterize the nature of correlated defaults, an essential input when trying to hedge or to pre-empt a future financial crisis. Coming down to the level of the firm, we will use the information provided by these indicators to decompose the credit risk of each firm into a systemic component, a sectorial component and an idiosyncratic component.

The key lesson learned from this crisis is that financial institutions need to have a comprehensive risk appetite framework in place that helps them better understand and manage their risks by translating risk metrics and methods into strategic decisions, reporting, and day-to-day business decisions [FBS (2013) and EBA (2014)]. Our analysis provides an element for such risk appetite framework. By providing an estimate of the global risk factor, analysing its determinants and using that factor to evaluate the systemic and the idiosyncratic components of risk, we describe an empirical framework that can be used by financial institutions to manage their risk. Indeed, the numerical estimates of risk components we propose for individual firms can easily be used by financial institutions to maintain their risk limits when taking their asset allocation decisions. It should also be a central input in the design of appropriate hedging strategies. Furthermore, by evaluating the firms and sectors with the most potential to produce systemic risk problems, our analysis should also be considered to be crucial for supervisors and regulators.

Even though we restrict our analysis to CDS issuers, further research should relate our estimated risk components to firms' characteristics such as size of assets and liabilities, profit and loss results, equity and bond prices, and market share. That would allow us to extend the risk evaluation results obtained for CDS issuers to any other firm.

The first part of our sample period includes the recent financial crisis, with intense monetary interventions taking place in the second part of the sample. Strong credit expansion at the beginning of the sample period was followed by acute stress in the global credit markets. Our analysis will allow us to address the following specific issues: What were the most systemic sectors during the 2006-2012 period? Which sectors allow for a more diversified credit portfolio? What are the most influential financial variables explaining credit spread movements? What is the decomposition of CDS spreads among systemic risk, sector risk and idiosyncratic risk? Can the use of credit indices provide an acceptable hedge for a diversified CDS portfolio? Is there a strong geographical factor in the intra-sector analysis of the different corporate sectors?

The paper is structured as follows: In the next section, we review the most relevant literature on this topic. In Section 3.3 we comment on some characteristics of the Markit database, the standard source for CDS market data. In Section 3.4 we analyse the commonality of credit risk across sectors and we estimate a global risk factor, characterizing some of its determinants in Section 3.5. In Section 3.6 we use the global risk factor to estimate systemic and idiosyncratic components of sectorial credit indices. In Section 3.7 we estimate the sensitivity of sectorial credit indices to financial indicators, in an attempt to advance factor models for sectorial risk. In Section 3.8 we decompose credit risk at the level of the firm among systemic, sectorial and idiosyncratic components. In Section 3.9 we address some issues justifying our strategy for the decomposition of credit risk. Finally, we conclude with a summary of the main findings.

3.2 Literature review

Given the importance of the topic for researchers and for market regulators after the financial crisis, the recent literature on measuring systemic risk has been quite extensive. We briefly review in this section the papers we consider most relevant for our work.

Using CDX and iTraxx Index data for the period 2005-2007, Bhansali et al. (2008) used a simple linearised version of a three-jump model of Longstaff and Rajan (2008), calibrated to the traded spreads of tranches and indices, to find that the credit loss distribution embedded in index tranche prices includes a component for the risk of idiosyncratic or firm-specific defaults, a component for the risk of broader sector-wide or industry-wide defaults, and a component for the risk of a massive economy-wide default scenario. They conclude that the nature of systemic credit risk increased dramatically over their sample period, having started as just a small percentage of total credit risk during the auto-downgrade credit crisis of May 2005. At a fundamental difference from previous credit crises, the systemic component of credit risk acquired an importance similar to the idiosyncratic component of credit spreads.

Using a sample of 150 European firms from January 2003 to July 2007, Berndt and Obreja (2010) showed that the first principal component of CDS returns explained less than 30% of the variation in weekly CDS returns, although such a fraction surged to 50% during the crisis from August 2007 to December 2008. The shift in the correlation structure of European equity returns was more modest when compared to CDS returns, their first principal component explaining about 33% of the total variation prior to August 2007, and 44% during the crisis. Using daily data from fifteen financial institutions from Europe and the US from January 2004 to June 2010, Giglio (2010) showed that the upturn in bond yields and CDS spreads of financial institutions during the crisis reflected increases in idiosyncratic default risk rather than systemic risk. This was the case for the months before the Bear Stearns episode in March 15, 2008, and also after Lehman's default. Chen and Härdle (2012) studied the 5-year and 10-year credit indices for investment grade and high-yield ratings between October 2004 and June 2011, to find that the market prices of risk factors estimated by the GMM method suggest that a four-factor model could provide a good fit when explaining changes in CDS indices. They also found that the first principal component for CDS indices explained 58.7% of the variance in the pre-crisis period, increasing up to 72.3% of the variance in the crisis period, but only 47% in the post-crisis period.

Rodríguez-Moreno and Peña (2013) analysed two groups of systemic risk measures when searching for the best systemic indicator over the January 2004-November 2009 sample period. A first group contained indicators related to the overall tension in the market, while a second group was made up by indicators related to the contributions of individual institutions to systemic risk. In a sample of twenty European banks and thirteen US banks they found that the first principal component of CDS spreads performed better than measures of market stress. Hammoudeh et al. (2013) examined the behaviour of the US 5-year sector CDS spread indices for banking, the financial services and the insurance sector over the period January 2004 to March 2009. The Insurance Sector Index had the largest long run adjustment of the three sectorial CDS indices. In the short run, the three CDS indices display significant and positive bidirectional relationships, implying that they feed on each other after changes in credit conditions. Finally, Puzanova and Düllmann (2013) present an approach for measuring systemic risk and decomposing it into the contributions of individual institutions. To assess the system-wide loss they modelled a banking sector as a portfolio comprising banks' net of capital liabilities, using a widely used credit risk model to assess the tail risk of such portfolio. The model inputs were the banks' individual probabilities of default, the size of their net of capital liabilities and the banks' sensitivity to systemic factors, which capture correlations between banks' asset returns.

This literature deals with some of the specific questions that we proposed in the introduction. For instance, Berndt and Obreja (2010) and Chen and Härdle (2012) try to characterize the most influential financial variables that explain credit spread movements by analysing the impact of some financial variables on individual CDS spreads or CDS indices, respectively. Our objective is somewhat different, as we use a large set of different financial variables in a more recent period of time to explain the corporate sector CDS indices according to the Industry Classification Benchmark. Bhansali et al. (2008) carried out a decomposition of CDS spreads among systemic risk, sector risk and idiosyncratic risk as we attempt to do in this paper, although their methodological approach is quite different: we use the principal component analysis instead of a three-jump model, with a different dataset to extract our conclusions. We are not aware that the rest of the questions raised in the introduction have been examined in detail before by other authors.

In addition to this review of recent literature, we also summarize in Section 3.5 the results of recent studies that have examined the determinants of CDS spreads.

3.3 Markit database

The database that we have used for this essay is provided by Markit, the main supplier of CDS prices [Markit (2008) and Markit (2012)]. The various fields that we have selected are ticker, tier, spread, sector and region. The ticker gives information on the key name of the issuer. Tier contains the type of debt that is to be delivered in the event of a default. This might be SEDCOM Secured Debt (Corporate/Financial), SNRFOR Senior Unsecured Debt (Corporate/Financial), SOVEREIGN Debt (Government), SUBLT2 Subordinated or Lower Tier 2 Debt (Banks), JRSUBUT2 Junior Subordinated or Upper Tier 2 Debt (Banks), and PREFT1 Preference Shares, or Tier 1 Capital (Banks).

Markit provides us with the information on the different CDS spreads with different tenors: 6M, 1Y, 2Y, 3Y, 4Y, 5Y, 7Y, 10Y, 15Y, 20Y, and 30Y. The most liquid CDS is the 5-year contract. All these prices are composite, that is, for a given restructuring event, issuer and currency, they are the average of prices provided by different financial institutions. Sector is based on the ICB classification, (Industry Classification Benchmark), which distinguishes four levels: Industry, supra-sector, sector, and subsector. We work with Markit industry level, which considers eleven industries: basic materials, consumer goods, consumer services, energy, financials, health care, industrials, technology, telecommunication services, utilities, and government.[1] Finally, Markit considers thirteen different regions: Africa, Asia, Caribbean, Eastern Europe, Europe, India, Latin America, Middle East, North America, Oceania, Offshore, Pacific and Supranational.

We select the set of 5-year CDS trading as senior unsecured debt, SNRFOR, with 1825 daily observations on approximately 2500 issuers from the eleven mentioned industries and the thirteen geographical areas, with

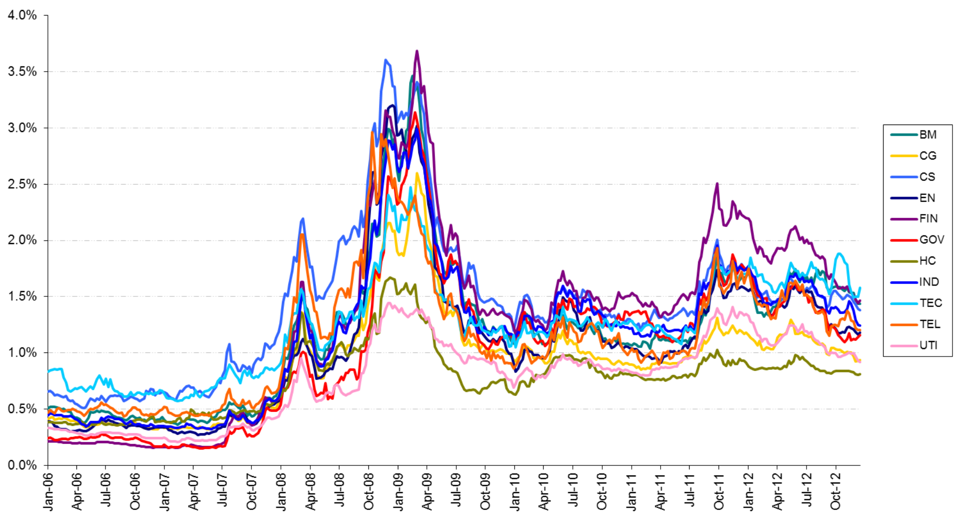
[1] Government is another category considered by Markit but not included in the Industry Classification Benchmark.

the disaggregation shown in Figures 1.2 and 1.3 in the first chapter. These figures display the distribution of CDS by ratings, sectors, and regions for a particular day, 31 January 2012. It can be seen that most of the issuers have ratings "BBB" or "A". The better represented sectors are financials, consumer services and industrials, while the main regions are North America, Europe, and Asia. Although we show the CDS distribution by rating, sector, and region for a particular day, these distributions are relatively stable through time. We consider the eleven sectors and thirteen geographical regions defined above. After that, we construct CDS indices for each sector by taking the median CDS spread traded each day in that sector across all regions. Then, we construct weekly sectorial data by taking the average of the daily observations over each week. Finally, weekly returns are obtained as logarithmic returns of weekly CDS spreads, obtaining a total of 365 weekly observations over the 2006-2012 period.

3.4 Inter-sector risk analysis

The first part of our analysis evaluates the systemic nature of risk at the level of global sector indices. We do so by searching for a global risk factor using the set of CDS trading in the different sectors in all regions, and estimating the degree of dependence of each sector on that global factor.

Figure 3.1: Sectorial CDS spreads



Note: Sectorial CDS indices. Weekly data

BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, and UTI = Utilities.

The origin of the financial crisis may be placed on August 9, 2007, with BNP Paribas announcing that it was ceasing activity in three hedge funds that specialized in US mortgage debt. The announcement acted as a signal that there were tens of trillions of US dollar worth of derivatives which were worth much less than previously estimated. Since nobody knew the exposure of individual banks to these toxic assets, trust evaporated overnight and banks stopped doing business with each other. The perception of risk spread over all sectors, which explains the simultaneous increase shown in Figure 3.1 in CDS spreads in all sectors after July 2007. They reached a local maximum on March 2008 and decreased for a while to start an even sharper increase in the summer of 2008 that would take them to maximum values during the first quarter of 2009. Spreads rapidly decreased after that, although they did not go back to the low levels prior to the 2007 crisis.

The rise in financial CDS spreads towards the end of 2010 is also clearly visible in the graph. CDS spreads are clearly non-stationary over the whole sample, while their weekly changes are stationary, as it can be confirmed from the application of Dickey-Fuller tests. There is a clear difference in the mean between the pre-2008 and the post-2009 periods, with an intermediate period of turmoil in 2008-2009. CDS returns experience different fluctuations across sectors. The higher volatility is achieved by spreads from the financials, telecommunication services and the government sectors [see Table 3.1].[2] Interestingly enough, all sectors display right skewness, while kurtosis is particularly high in the financials, health care and government sectors. As a consequence, the assumption of normality is clearly rejected as the distribution of CDS spreads in all sectors.

Table 3.1: Sectorial returns. Main statistics

Returns	BM	CG	CS	EN	FIN	GOV	HC	IND	TEC	TEL	UTI
Maximum	0.196	0.185	0.178	0.240	0.298	0.342	0.228	0.185	0.164	0.203	0.195
Minimum	-0.142	-0.162	-0.150	-0.180	-0.164	-0.218	-0.206	-0.151	-0.113	-0.192	-0.110
Range	0.338	0.347	0.329	0.420	0.462	0.559	0.434	0.336	0.277	0.395	0.305
Standard Deviation	0.047	0.044	0.044	0.046	0.053	0.060	0.043	0.046	0.044	0.058	0.039
Volatility	33.7%	31.7%	31.5%	33.5%	38.1%	43.6%	31.2%	33.3%	31.9%	42.0%	28.3%
Skewness	0.636	0.593	0.353	0.790	1.422	1.118	0.600	0.669	0.218	0.596	1.211
Excess kurtosis	1.596	2.543	1.392	3.455	6.318	5.240	6.079	2.162	0.594	1.449	4.533
Beta-Jarque Statistic	63.2	119.4	37.0	218.8	728.2	492.3	582.4	98.1	8.2	53.4	400.6

Note: Returns main statistics for each sector. BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, and UTI = Utilities.

[2] Volatility might seem lower than it is usually associated to credit returns. That is because we deal with log-returns on indices that have been constructed as the weekly average of the median of daily traded CDS spreads.

Table 3.2: Sectorial correlation matrix

Sector	BM	CG	CS	EN	FIN	GOV	HC	IND	TEC	TEL	UTI
BM	100%	76%	69%	70%	69%	64%	50%	78%	57%	64%	66%
CG	76%	100%	74%	72%	78%	68%	52%	82%	58%	69%	73%
CS	69%	74%	100%	68%	66%	59%	47%	74%	48%	69%	65%
EN	70%	72%	68%	100%	76%	65%	50%	73%	54%	67%	74%
FIN	69%	78%	66%	76%	100%	75%	52%	78%	55%	68%	77%
GOV	64%	68%	59%	65%	75%	100%	40%	69%	49%	58%	68%
HC	50%	52%	47%	50%	52%	40%	100%	54%	38%	46%	51%
IND	78%	82%	74%	73%	78%	69%	54%	100%	56%	69%	73%
TEC	57%	58%	48%	54%	55%	49%	38%	56%	100%	53%	51%
TEL	64%	69%	69%	67%	68%	58%	46%	69%	53%	100%	68%
UTI	66%	73%	65%	74%	77%	68%	51%	73%	51%	68%	100%
Median	69%	73%	68%	70%	75%	65%	50%	73%	54%	68%	68%

Note: Pairwise correlation matrix between sectorial index returns. BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, UTI = Utilities, and MCS = Median intra correlation for each sector.

Table 3.2 displays linear correlation coefficients among weekly changes in CDS spreads, showing significant correlations across all sectors. Median correlations for each sector are around 0.70, except for health care and technology [the last row in the table]. These are the sectors with lower correlations with the rest of the sectors, with a median correlation around 0.50 and hence, they should be expected to be the less systemic sectors. The high overall correlations reflect the existence of at least a common factor, while the existence of specific factors explaining fluctuations in CDS prices in health care and technology sectors may explain the lower association between these two sectors and all the others. To explain CDS spreads in these sectors, more than one risk factor may be needed.

We characterize common risk factors among CDS spreads from the different sectors using the principal component methodology.[3] The first principal component, by itself, explains 68% of the fluctuations in the set of eleven sectorial indices, indicating that there is strong commonality among the sectors. This is a higher percentage than the one estimated by Berndt and Obreja (2010) for European firms during the 2003 to 2008 period, but it is very close to the average explanatory power estimated by Chen and Härdle (2012) for the pre- (58.7%) and post-crisis periods (72.3%).

Since the first principal component explains more than two thirds of the fluctuations in the whole set of CDS issues from all sectors and geographical areas, it can naturally be interpreted as representing a global risk factor. On the other hand, there seems to be enough specific fluctuation in some sectors that we would need a relatively large number of components to explain a percentage of variance of the order of 90% or 95%.[4]

[3]We apply this methodology to the covariance matrix of weekly returns on CDS. Characterizing principal components to the correlation matrix of CDS returns would produce somewhat different results. As is well known, using the covariance matrix will tend to suggest a more relevant role to those sectors with higher volatility.

[4]Cumulative percentage of total variance explained by the principal components is 67.9% for the first one, 74.3% for the first two, 79.3% for the first three principal components, and 83.9% for the first four.

An examination of the principal component loadings shows that the first principal component is, approximately, an average of CDS returns over all the sectors, although with a slightly weaker presence of the health care and technology sectors. These two sectors dominate the third and fourth principal components, respectively, while the second component is dominated by the government and telecommunication services sectors. Hence, those sectors with a lower representation in the first principal component, health care and technology, can be unquestionably associated with two other principal components. It is interesting to note that the government sector seems to have a strong specific behaviour that explains its association with the second principal component in spite of having a loading in the first component in line with that of the other sectors. Principal components after the first four are much harder to interpret.

These four principal components we have just described, taken together, contain high explanatory power for most sectors, as shown in Table 3.3, which displays R-squared statistics from regressions s on an increasing number of the first six principal components. However, specific additional factors seem to still be needed to explain the fluctuations in CDS spreads from utilities and energy. As expected, adding the second component to the regression increases the fit for the government sector, while adding the third one produces a large improvement in the fit of the health care sector and adding the fourth component increases the fit of the technology sector.

Table 3.3: R-squared coefficients in regressions as principal components are added as explanatory variables

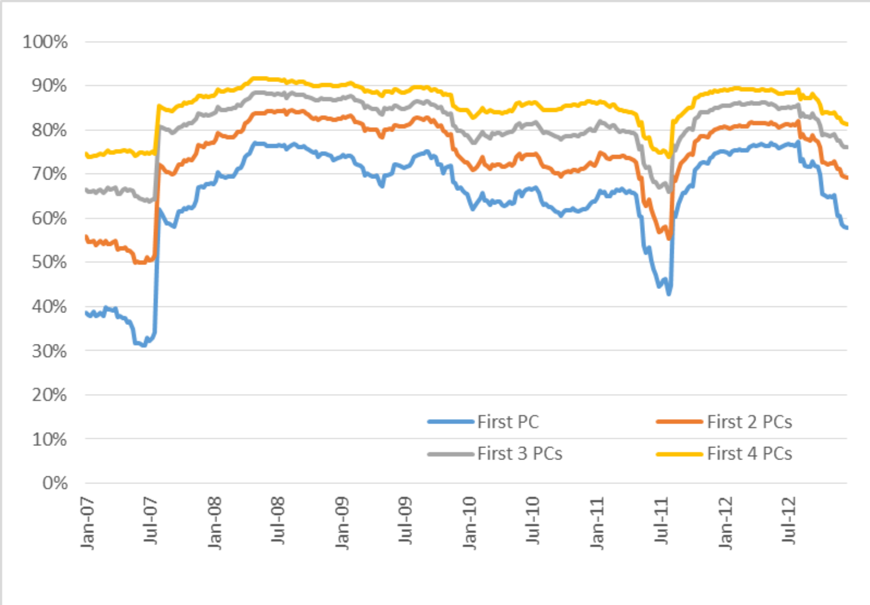
	PC1	PC12	PC123	PC1234	PC12345	PC123456
BM	71.2%	71.7%	72.2%	73.7%	84.4%	85.9%
CG	79.0%	79.1%	79.2%	79.3%	82.6%	82.6%
CS	66.5%	69.2%	69.9%	71.4%	79.1%	81.5%
EN	72.8%	72.9%	72.9%	73.1%	73.1%	85.1%
FIN	80.0%	82.0%	82.3%	82.8%	83.3%	89.3%
GOV	67.8%	94.5%	94.6%	94.6%	96.1%	99.4%
HC	37.3%	46.1%	87.4%	89.3%	97.0%	99.8%
IND	79.9%	80.0%	80.5%	80.5%	84.7%	84.7%
TEC	44.9%	46.4%	46.4%	96.1%	98.8%	98.8%
TEL	68.7%	78.4%	91.9%	93.6%	98.3%	99.2%
UTI	71.3%	71.4%	71.4%	72.6%	73.0%	77.2%

Note: The first column shows R-squared of a regression on the first principal component as the single regressor (other than a constant). The second column shows the R-squared from a regression on the first two principal components, and so on.
BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, and UTI = Utilities.

But how did the crisis affect the different sectors? In so far as the effects were felt over the whole economy, we should expect to see the common factors increasing their relevance in that period of time, dominating sector-specific risk elements. To check that hypothesis, we follow Eichengreen et al. (2012) to use annual windows to estimate the percentage of total variance in the set of CDS returns for the eleven sectors which is explained by the first principal component. Estimates start the first week of January 2007, running to the end of December 2012, each estimation in Figure 3.2 being obtained with the sample made up by the 52 previous weekly data.[5]

[5] Note that the trend of this figure is very similar to Figure 5.7 in the last chapter.

Figure 3.2: Cumulative information content in the first four principal components of sectorial returns.



Note: Weekly data: January 2007-December 2012. The figure shows the percent variance of the set of sectorial credit returns that is explained by the first k principal components of sectorial credit indices, k=1,2,3,4.

At the beginning of 2007, the first common factor explained almost 40% of the total variation in sectorial CDS indices, with the first four factors explaining 75% of total variance. The explanatory power of the first principal component jumps from 32% in July 13, 2007, to 62% in August 20, 2007 at the outbreak of the subprime crisis after the failure of three hedge funds at BNP Paribas. The increase in explanatory power did not stop there: the Bear Sterns rescue on March 2008 produced a sharp increase in the perception of risk across the economy, as reflected in CDS spreads for all sectors of activity. Consequently, the explanatory power of the first common factor continued on a gradual increasing trend to a local maximum of 77% on the week of May 9, 2008, well before Lehman's failure. The continuous increase in the commonality of risk from May 2008 could have been taking as an indication of potential future problems well in advance of the Lehman crisis. These results are comparable to those obtained by Berndt and Obreja (2010) and Chen and Härdle (2012), among others.

A sharp decrease was again observed from March 2011. On March 11, the EU decided to allow the European Financial Stability Facility (EFSF) to buy debt in primary markets up to a 440 billion euros ceiling. It also resolved to cut the rates and extend the maturities of the emergency loans to Greece. On the 21th, the EU summit agreed on a permanent bailout mechanism for the region to lend up to 50 billion euros starting on May 2013.The commonality in sectorial CDS indices declined from their peaks but remained at the post-Bear Stearns elevated levels, indicating that risk was widespread across the sectors. The explanatory power of the first common factor fell drastically to 43% on August 5, 2011. The bail out of Portugal on May 5 and the rating cut for Greece on June 13 did not have a visible effect on the explanatory power of the common factors. On the other hand, the downgrade of US debt on August 5, the deterioration of the economic situation in the US, the alarm on a potentially catastrophic credit crisis in Europe and the downgrade of sovereign debt in southern European countries explain the increase in the commonality of risk observed in the second part of the year to levels of 75% by the end of 2011. From that point on, the explanatory power gradually decreased to levels of 60% at the end of our sample one year later.

3.5 Factors underlying the global risk factor in CDS spreads

Motivated in part by the financial crisis, the study of the possible determinants of CDS spreads has been very popular over recent years, and many papers have been devoted to this issue from different perspectives.

Ericsson et al. (2009) used CDS data on senior debt for 1999-2002 to confirm the relevance of some theoretical determinants of default risk, such as the firms' leverage, market volatility, the level of the risk-free interest rate, and the actual market premium. They found that these variables explained approximately 60% of the variation in the levels of CDS premia, with an R-squared for changes in default swap premia of approximately 23%. Using transactions data from 2002-2009 covering 861 North American corporates, Tang and Yan (2013) found that CDS spreads were mostly driven by fundamental variables such as firms' volatility and leverage, market conditions as the VIX Index, the swap rate, the term structure slope, stock prices and CDS liquidity, as indicated by the bid-ask spread, and investor risk aversion, with excess demand for CDS contracts playing a secondary role. Even if the level of default risk stays the same, CDS spreads may increase when investors become more pessimistic and more risk averse. Indeed, a 1% increase in the VIX Index, the so-called "fear factor" often used to measure market sentiment or average investor risk aversion, is associated with about a 1% increase in CDS spreads. With R-squared estimates around 30%, changes in volatility for the firms' stock seem to be one of the main determinants of the level of CDS spreads, with a one standard deviation increase in stock volatility leading to a 12.5% increase in CDS spreads. This result is consistent with those of Campbell and Taksler (2003), Ericsson et al. (2009), and Zhang et al. (2009).

Pires et al. (2013) use a quantile regression approach to analyse the explanatory power in variables such as implied volatility, the put skew, historical stock returns, leverage, profitability, and ratings. These authors find that illiquidity costs, measured by absolute bid-ask spreads are an important determinant of CDS spreads, with spreads for high-risk firms being more sensitive to these factors than those from low-risk firms. They also find that the explanatory power of the set of factors increases with CDS premiums, in consistency with the credit spread puzzle. Finally, Hull et al. (2004) analysed a large panel of US and European corporate issuers to find that there is an anticipation of rating announcements by the credit default swap market.

Our approach is somewhat different, since we work in this section with aggregate CDS spreads at the level of sectors. The reason for that aggregation is to eliminate some of the noise that appears in individual firm data. This way, we lose information on individual CDS, which precludes from examining interesting issues like the relationship between CDS spreads and equity prices [see Blanco et al. (2005)] or the relevance of a firm's fundamentals and accounting data to explain variations in CDS spreads. To cover our goal of estimating the relative size of the systemic and idiosyncratic components of CDS risk, we have already advanced how the global risk factor, estimated in the previous section as the first principal component for the set of eleven sectorial indices, is clearly an element of systemic risk in CDS spreads that captures the main aspects of fluctuations in CDS spreads across sectors. We now want to explore what underlies the behaviour of this global risk factor by looking at its correlations with financial indicators, which might suggest possibilities of anticipating changes in CDS spreads.

To derive a fundamental interpretation of the estimated global risk factor, we use a list of financial factors from Bloomberg.[6] These are 1) 3-month EURIBOR interest rate (EUR3m), 2) 3-month EONIA Index, 3) EUR liquidity premium, measured by the absolute difference between 3-month EURIBOR and 3-month EONIA, both in euros (Liq_EUR), 4) 1-year EUR Swap Rate (EUR1y), 5) 5-year EUR Swap Rate (EUR5y), 6) 10-year EUR Swap Rate (EUR10y), 7) 3-month/ 5-year ATM EUR Swaption (3m5yEUSwap), 8) VSTOXX Index (EUR) (VSTOXX) 9) 5-year German Government Yield (GDBR5), 10) 3-month USD LIBOR Interest Rate (Lib3m), 11) 3-month USD Overnight Index (3-month USD ONIA), 12) USD liquidity premium, measured by the absolute difference between 3-month LIBOR and the 3-month USD Overnight Index (Liq_USD), 13) 1-year USD Swap Rate (USD1y), 14) 5-year USD Swap Rate (USD5y), 15) 10-year USD Swap Rate, 16) 3-month/5-year ATM USD Swaption (3m5yUSwap), 17) VIX Index (USD) (VIX), 18) 5-year US Treasury Rate (UST5), 19) EUR/USD FX Spot Rate (EUR/USD), 20) EUR/USD 3-month ATM option (FXImVol), 21) Markit iTraxx Europe Index (iTraxx), 22) Markit iTraxx Europe HiVol Index (HiVoliTraxx), 23) Markit CDX North American Investment Grade Index (CDX), 24) Markit CDX North American Investment Grade Index High Yield (CDXHY), 25) 3-month ATM iTraxx Europe Index Option (iTraxxImVol), 26) 3-month ATM CDX North American Investment Grade Index Option (CDXImVol), 27) iTraxx Japan IG (iTraxxJP), 28) 5-year JPY Swap (JP5y) and the ten MSCI stock market sector indices.[7]

The global risk factor, measured as the first principal component across sectors, displays high and positive correlations with all credit indices: iTraxx, CDX, iTraxxJP, HiVoliTraxx, and CDXHY, in consistency with the interpretation we have given to this component as summarizing the global characteristics of the credit market. It also has positive correlation with volatility indicators: VIX, VSTOXX, CDXImVol, iTraxxImVol, and a somewhat lower correlation with the volatility of the euro-dollar exchange rate. It again displays positive but weaker correlations with the euro and US swaption rates, as well as with the two illiquidity indicators we consider (spreads to EONIA rates of EURIBOR and LIBOR rates). Finally, the first principal component is negatively correlated with interest rates, swap rates and US and German government rates. A negative correlation between CDS premia and some interest rates was also documented for bond yield spreads by Longstaff and Schwartz (1995) and also by Ericsson et al. (2009), while the positive correlation with stock market volatility has also been documented when working with single CDS spreads in some of the references mentioned above. Furthermore, all estimated correlations display the expected signs.

We will now structure these correlations in a regression model that might help us understand the factors

[6] The 3-month ATM iTraxx Europe Index Option and the 3-month ATM CDX North American Investment Grade Index Option are provided by JP Morgan.

[7] These are: MSCI World/Basic materials, MSCI World/Consumer goods, MSCI World/Consumer services, MSCI World/Energy, MSCI World/Financials, MSCI World/Health care, MSCI World/Industrials, MSCI World/Technology, MSCI World/Telecommunication services and MSCI World/Utility.

that influence the evolution of global credit risk. A simple regression to explain the time evolution of the global risk factor, with iTraxx as the only explanatory variable attains an R-squared of 0.604 [first column in Table 3.4].[8] With the CDX Index as the only explanatory variable, the R-squared is somewhat lower, of 0.544 (not shown in the table). However, the information content in credit indices on the global risk factor is almost tautological, since both are sort of an average of CDS spreads across all sectors.

The second regression also shows a relatively high adjusted R-squared statistic without using any credit index. The global risk factor increases with implicit credit market volatility, with stock market volatility, as measured by VIX, and with exchange rate volatility. It also responds positively to the 5-year US swaption rate. On the other hand, the global risk factor moves contrary to the 5-year yield on US Treasury bonds, the overnight rate, the spread between 3-month EURIBOR and EONIA rates, and the euro-dollar exchange rate. It also shows an interesting response to changes in the term structure, decreasing when the spread between 10- and 5-year US swap rates increases or when the spread between 5- and 1-year swap rates decreases.

Figure 3.3 shows the global risk factor and its adjusted values from this regression. We can see that the regression model does a good job in explaining the wide fluctuations in the risk factor during the crisis, which is precisely when such a model is needed, while in quiet periods, the explanatory power is relatively minor.

Hence, the global risk factor we have estimated basically reflects events affecting credit market volatility, and it is associated with changes in interest rates, as well as with rates of return and volatility indicators from some financial assets, as shown in the regression in Table 3.4. From the point of view of the hedging possibilities for credit positions, the second regression in the table is quite interesting, since it suggests that a credit portfolio might be hedged in part by taking appropriate positions in interest rate and volatility derivatives. To that end, it is worthwhile to emphasize that the global risk factor increases with stock market or credit market volatility, and it decreases when interest rates increase.

Another interesting fact is that the set of financial indicators described above does not have a significant explanatory power for the remaining principal components. For instance, all of them together explain just 12% of the fluctuation in the second principal component and 5% of the third and the fourth components. In particular, this result means that whichever specific component there may be in CDS returns from the government, the technology or the health care sectors, is not of a financial nature. They might be related to macroeconomic factors or to firm characteristics that we have not taken into account in our analysis.

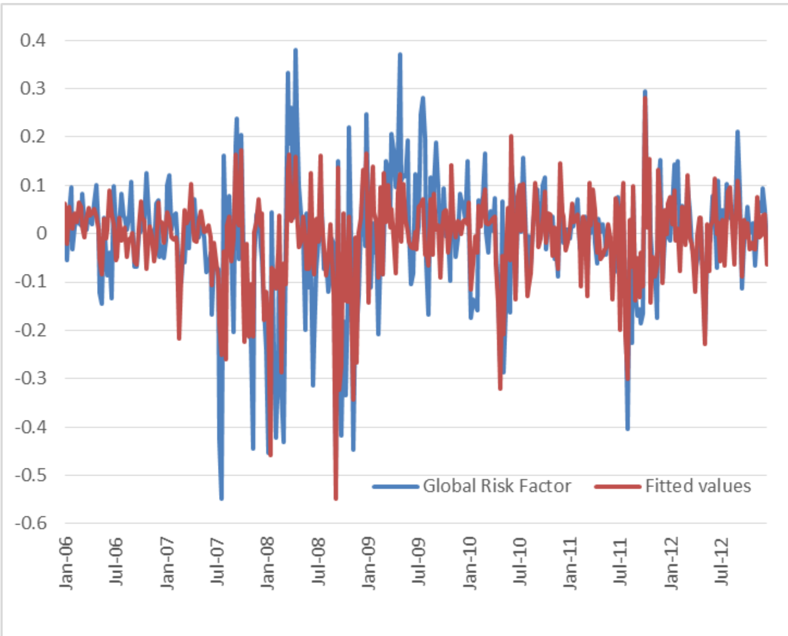
[8] A constant term is always included in all the estimated regressions.

Table 3.4: Regressions explaining the global risk factor

Variable	Full Sample	Full Sample	Jan. 2006 - Dec. 2008	Jan 2009 - Dec. 2012
iTraxx	0.0132 (23.48)			
CDXImVol		0.448 (3.15)	0.355 (1.77)	0.613 (3.24)
iTraxxImVol		0.138 (1.12)	0.277 (1.52)	-0.228 (1.57)
VIX		0.007 (3.14)	0.008 (2.28)	0.009 (2.86)
FXImVol		0.015 (1.82)	0.021 (1.80)	0.004 (0.31)
USD1y		-0.279 (2.05)	-0.199 (0.96)	0.110 (0.52)
USD5y		1.321 (4.94)	1.239 (2.89)	1.246 (3.96)
USD10y		-0.761 (4.90)	-0.706 (2.74)	-0.734 (4.37)
3-month USD ONIA		-0.261 (1.82)	-0.251 (1.32)	-1.205 (1.67)
3m5yUSwap		0.003 (3.93)	0.003 (2.74)	0.001 (1.09)
UST5		-0.838 (5.15)	-0.900 (3.97)	-0.628 (2.53)
EUR/USD		-0.858 (2.62)	-0.921 (1.71)	-1.128 (2.96)
Liq_EUR		-0.201 (1.87)	-0.272 (1.79)	0.015 (0.10)
AdjR-Squared	0.604	0.510	0.468	0.653

Note: The global risk factor is estimated as the first principal component over the set of sectorial index returns. A constant term is included in each regression. t-values are shown in parenthesis.

Figure 3.3: Global risk factor: observed data and fitted values.



Note: The figure shows global risk factor data together with the fitted values from regression in column 3, Table 3.4. Weekly data: January 2006 - December 2012.

The last two columns in the table show that the full sample estimates of the indicators regression is essentially determined by the relationship between the global risk factor and the set of financial indicators during the crisis (2006-2009). The relationship after 2010 is somewhat different, with a similar role for credit volatility (the sum of coefficients on ivolCDX and ivoliTraxx) a weaker relationship with exchange rate volatility, the swaption rate and the liquidity in the Eurozone. However, the structure of the relationship is quite stable and the Chow test does not detect a structural change between the two subsamples.

3.6 Systemic and idiosyncratic risk at the level of sectors

For asset allocation purposes, it is central to have some knowledge of the nature of risk involved in a given credit position. In this section we advance in such analysis at the level of sectors, by decomposing the risk of a sectorial credit portfolio into systemic and idiosyncratic risk components. Such decomposition will directly give us an indication of the possibilities for diversifying risk in that portfolio by taking positions in other sectors, thereby being a crucial element in any risk appetite framework.

Our approach to decompose risk is based on the use of the set of financial indicators described in the previous section. Our suggestion is to split the set of indicators into a block of 6 indicators from credit markets (iTraxx, HiVoliTraxx, CDX, CDXHY, CDXImVol, iTraxxImVol), and a second block of 30 indicators from financial markets other than credit: the 3-month EURIBOR Rate, 3-month EONIA Index, the Euro liquidity premium, the 1-, 5- and 10-year EUR Swap Rates, the 3-month/5-year ATM Euro Swaption Rate, the VSTOXX Index, the 5-year German Government Yield, 3-month USD LIBOR Interest Rate, 3-month USD Overnight Index, the USD liquidity premium, the 1-, 5- and 10-year USD Swap Rates, 3-month/5-year ATM USD Swaption Rate, the VIX Index, 5-year US Treasury Rate, EUR/USD FX Spot Rate, the EUR/USD 3-month ATM option, and the ten MSCI stock market sector indices. Then, we estimate principal components for each group of indicators. Two of these components in the subset of credit market variables and three principal components in the subset of other financial indicators explain more than 98% of the fluctuations in their respective groups.

The R-squared in a linear projection (regression) of each sectorial CDS index on the two principal components for credit market indicators could be taken as an approximation to the relevance of the credit element of risk for that sector. Similarly, a regression of CDS indices on the three principal components for the remaining indicators would give us an upper bound on the relevance of financial non-credit sources of risk.

Columns 2 and 3 in Table 3.5 present the relevance of credit risk and financial risk, while column 4 presents their joint explanatory power. We can see that credit risk indicators have twice as much explanatory power as non-credit financial indicators. Column 5 ('GRF') displays the information content in the global risk factor estimated in Section 3.4, showing that this factor has significantly higher explanatory power than the set of financial indicators, a result in line with Rodríguez-Moreno and Peña (2013). Column 6 ('Systemic') displays R-squared values for regressions on credit, non-credit indicators, and the global risk factor used together as explanatory variables. We take this linear projection as an estimate of the systemic component of risk in each sector. Finally, column 7 is equal to 1.0 minus the adjusted R-squared statistics in column 6, and it can be interpreted as the relevance of the idiosyncratic component of sectorial risk, since we have excluded all the systemic indicators captured by the global risk factor and the financial credit and non-credit financial indicators.

A comparison of columns 5 and 6 shows that the set of financial indicators does not add explanatory power to the global risk factor. This is a striking result showing that the global risk factor estimated in Section 3.4 captures different types of information, and it can act as a sufficient statistic for a wide set of credit and non-credit financial indicators when characterizing the nature of sectorial risk. In fact, a projection on the global risk factor alone could also be said to provide an estimate of the systemic component of risk, with practically the same decomposition as that shown in the table. There is also an important difference between both regressions: fitted values in column 5 refer to a component of global risk that might possibly be hedged by using appropriate derivative instruments defined over the set of indicators used in that regression. On the other hand, fitted values in column 6 could not possible hedged, since the global risk factor does not trade in any market.

Since each sector index has the nature of a relatively diversified credit portfolio, it is not surprising that idiosyncratic risk amounts to less than one third of total risk in all sectors except for health care and technology, in which we already detected in Section 3.4 the existence of an strong idiosyncratic element. Health care and technology are the two sectors that would be in less need for a hedge, while for all other sectorial investments the systemic component is large enough to suggest a strong need for hedging portfolios. To that end, it is convenient to know the sensitivities of sectorial CDS returns to different sources of risk, as captured by a variety of financial indicators. That is the object of next section.

Table 3.5: Decomposition of sectorial risk in systemic and idiosyncratic components

Sector	Credit	Financial	Joint	GRF	Systemic	Idiosyncratic
BM	42%	18%	43%	71%	71%	29%
CG	50%	19%	50%	79%	79%	21%
CS	48%	21%	48%	66%	67%	33%
EN	47%	24%	48%	73%	73%	27%
FIN	52%	29%	54%	80%	80%	20%
GOV	34%	17%	34%	68%	69%	31%
HC	27%	7%	27%	37%	38%	62%
IND	47%	17%	47%	80%	80%	20%
TEC	27%	13%	28%	45%	44%	56%
TEL	51%	26%	52%	69%	70%	30%
UTI	43%	20%	44%	71%	72%	28%

Note: Columns 2 and 3 show adjusted R-squared statistics for regressions of sectorial CDS indices on two and three first principal components of credit and non-credit financial indicators, respectively. Column 4 shows the adjusted R-squared of a regression on the five principal components together. Column 5 shows adjusted R-squared of a regression on the global risk factor, while column 6 shows the adjusted R-squared on a regression that includes the global risk factor and the five principal components as explanatory variables. Column 7 is equal to 1.0 minus the adjusted R-squared in column 6.

BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, and UTI = Utilities.

3.7 Sectorial sensitivity of CDS returns to risk factors

In this section we come down to the level of the sector, and study which specific factors, among the set of financial indicators we consider, explain CDS spreads in each sector. This is a very relevant issue to characterize the level and the type of risk in a sectorial position in CDS, and it is of utmost importance for trying to design a hedge on such a position. It would also be pertinent for a dynamic management of credit value adjustment (CVA) in any financial institution. Once we characterize the relevant factors for each sector, any anticipation of an increase or decrease in them might suggest an adjustment in the credit position or a change in the hedge for that position. In fact, we could think of designing a hedge on a sectorial CDS position by taking an adequate position in a relevant risk factor, whenever possible.

To evaluate the characteristics of the type of risk involved in a sectorial credit position we start by showing, in the second column in Table 3.6 estimates of beta-coefficients with respect to the iTraxx Index, a natural choice as a risk factor. As we can see, estimated betas lie in the (0.30; 0.50) interval, with R-squared values (column 6 'iTraxx') between 0.25, approximately, for health care and technology, the two sectors with a more important specific component, and up to 0.50 or even higher for the consumer goods sector, telecommunication services and the financial sector. Since our sample includes European and North American issuers, it is not surprising that the CDX IG Index also has a noticeable explanatory power (not shown in the table). Besides, it is well known that both indices are very highly correlated.

An obviously important question for risk management relates to the performance of a delta-hedging strategy for a CDS position in a given sector, based on taking a contrary position in the iTraxx Index, using the least-squares estimate of beta for that sector. Under that hedging strategy, the residuals from these regressions would be the returns of the hedged portfolio. Hence, the relationship between the residual variance and the variance of the sectorial index itself provides an indication of the efficiency of the hedge.[9] Columns 3 and 4 in Table 3.6 show the standard deviations of weekly changes in CDS for each sector, as well as the standard deviation of the residuals from regressions of the sectorial index on iTraxx. We can see that except for health care and technology sectors, hedging efficiency would lead to a reduction of about 70% or higher in return variance, a substantial decrease that shows an interesting potential for hedging credit portfolios when they are sufficiently diversified in a given sector.

Table 3.6: Regressions explaining sectorial credit indices

Sector	Beta	SD Returns	SD Residuals	Hedging Efficiency	Adjusted R-squared coefficients		
					iTraxx	GRF	Indicators
BM	0.360	0.047	0.025	72%	0.354	0.712	0.314
CG	0.399	0.044	0.020	79%	0.493	0.789	0.374
CS	0.359	0.044	0.025	68%	0.404	0.664	0.337
EN	0.380	0.046	0.024	73%	0.399	0.727	0.356
FIN	0.504	0.053	0.024	79%	0.546	0.800	0.539
GOV	0.456	0.061	0.034	69%	0.339	0.677	0.345
HC	0.281	0.043	0.034	37%	0.251	0.372	0.139
IND	0.404	0.046	0.021	79%	0.458	0.798	0.375
TEC	0.291	0.044	0.033	44%	0.258	0.447	0.237
TEL	0.533	0.058	0.033	68%	0.500	0.686	0.395
UTI	0.342	0.039	0.021	71%	0.456	0.712	0.396

Note: Column 2 shows the beta coefficient in regressions from sectorial index returns on weekly changes in iTraxx. Columns 3 and 4 display the standard deviations of sector index returns and the residuals from regressions on iTraxx, respectively.
Hedging Efficiency in Column 5 is equal to one minus the ratio of residual variance to variance of index returns.
Columns 6 and 7 show adjusted R-squared from regressions of sectorial index returns on iTraxx and the global risk factor, respectively.
Column 8 shows the adjusted R-squared from a regression on a set of indicators mentioned in the text.
BM = Basic materials, CG = Consumer goods, CS = Consumer services, EN = Energy, FIN = Financials, GOV = Government, HC = Health care, IND = Industrials, TEC = Technology, TEL = Telecommunication services, and UTI = Utilities.

[9]Even though this would be an in-sample evaluation, obtained as if the hedge could have been computed at each point in time having the information in the full sample, which is clearly unrealistic. Alternatively, this analysis could be performed using a bivariate GARCH methodology for each CDS index and iTraxx that would allow for time variation in variances and correlations.

The second regression explains sectorial credit indices with the global risk factor from Section 3.4 as the single explanatory variable (column 'GRF' in Table 3.6). We have already argued in the previous section that this latent variable captures risk elements from the credit market but also from other financial markets and possibly even from the real economy. The fact that the global risk factor contains a good deal of information on fluctuations in sectorial CDS returns is to be expected, but it is surprising that it contains so much more explanatory power than credit market indices. Its high information content may arise because by averaging CDS spreads over the sectors, the first principal component incorporates some aspects of the credit market that might be sector-specific and not incorporated in standard credit indices. Furthermore, the iTraxx may contain some idiosyncratic component unrelated to any specific sector, as reflected in the fact that it often presents deviations from the theoretical price that could be estimated from prices for its constituents, and that might weaken its correlation with sectorial credit indices.

The regressions we estimated in the previous section to explain the global risk factor suggest the possibility of constructing some relatively simple factor models for sector indices as well. To that end, we consider a regression model for weekly changes in each sectorial credit index using the same set of explanatory variables in the second regression in Table 3.4, which is now estimated for each individual sector under label 'Indicators' in Table 3.6. Adjusted R-squared statistics increase relative to the simple regression on the iTraxx Index, but they fall short of the level of R-squared statistics obtained when using the global risk factor as the single explanatory variable.[10] In fact, the global risk factor contains more information on sectorial credit indices than the whole set of explanatory variables we consider, which include credit indices together with a variety of financial indicators. Even using all of them together in a single regression we would not achieve an adjusted R-squared as high as those in column GRF.

Another interesting fact is the inability of the MSCI stock market indices to capture a significant amount of fluctuation in sectorial CDS spreads. When their weekly changes or their weekly returns are used by themselves to explain weekly changes in CDS spreads, R-squared values fall between 10% for the health care sector and 37% for the financial sector. Therefore, they have significant explanatory power. However, when added as explanatory variable to a regression of sectorial CDS indices on iTraxx, they barely add any improvement in fit.

From these results, an investor in the credit market would like to be able to hedge a credit portfolio using a contrary position on the global risk factor, given its high correlation with each sectorial index. Unfortunately, that factor, obtained as the first principal component of sectorial credit indices, is not linked to any specific asset, so it would not be possible to design a hedging strategy that would exploit its high correlation with most sectorial CDS indices. Our analysis just suggests the convenience of having good forecasting models for the global risk factor or for the set of explanatory variables in the regressions in the previous table, to infer from their predictions the expected change in CDS spreads ahead of time. Whether or not that is possible is left for further research.

[10]However, it is also conceivable that alternative combinations of the set of financial indicators we consider could be found having a similar explanatory power to the last regression in the table.

3.8 Decomposition of risk in specific sectors: systemic, sectorial and idiosyncratic risks

In previous sections we have analysed the nature of credit risk in sectorial portfolios. Such information is needed for a rigorous asset allocation of credit among sectors. We now come down to the analysis of the characteristics of risk in some specific sectors, which should be the guide for asset allocation decisions inside a given sector. We want to measure to what extent firms in the sector are subject to systemic risk as well as to sectorial risk and what the relevance of idiosyncratic risk is. We count as systemic risk events that have influence across the global credit markets. By sectorial risk we understand events that affect all firms in the sector, with no essential effect elsewhere. The idiosyncratic component of risk is obtained as the residual of each firm CDS return after extracting the systemic and sectorial components of risk. Such evaluation of the relevance of risk components has obvious implications on the asset allocation strategy by a given financial institution that wants to diversify its credit portfolio in that sector. In designing their credit policy, financial institutions should avoid firms with a large systemic risk component in favour of those with larger idiosyncratic risk components, always trying to form sufficiently diversified portfolios. As a byproduct, we also want to analyse whether the risk structure is common to a given sector in different geographical areas, such as the financial sectors of Europe and North America. That might suggest that sectorial characteristics are possibly more important than geographical characteristics in determining CDS spreads.

To estimate the systemic component of risk we will use the same approach as with the sectorial indices, based on principal component estimates for the credit and the non-credit financial indicators separately. Once we have an estimate of the systemic risk component, we estimate a regression of CDS spreads on the systemic component plus the first intra-sector principal component of CDS spreads. For each sector, this principal component will contain some features common across firms in the sector, possibly together with some elements of systemic risk. Subtracting from the joint explanatory power, measured by the adjusted R-squared, that of the systemic component alone, we will have an estimate of the relevance of sector-specific risk. What is left to 100% is an estimate of the size of the idiosyncratic component of risk for each issuer. The residual in the last regression can be taken as an estimate of the idiosyncratic risk component.

3.8.1 European industrial sector

In the European industrial sector, the sample is composed by the 30 issuers that had a quoted price every day during the period 2006-2012.[11] The first among the 30 principal components explains 64.4% of the fluctuation in CDS prices, while the first six principal components explain above 80% of the joint volatility in CDS prices. As usual, the first component is an approximate average of CDS prices across the sector, with all the firms entering with a similar load in that first component. Firms like Rentokil Initial 1927 Plc, Heidelberg Cement AG, Invensys plc, Alstom and Siemens AG have a significant presence in defining the successive principal components. This

[11] For example Banco Santander is not included in the European financial sample as Banco Santander changed its social denomination from Banco Santander Central Hispano to Banco Santander on 13 August 2007, consequently changing its company ticker.

intra-sector first principal component has a linear correlation coefficient with the iTraxx Index of 0.72, showing that there are significant sectorial and idiosyncratic elements of risk in the sector.

Table 3.7 shows an estimation of the percentage of the fluctuation in CDS prices for each issuer that can be attributed to systemic factors, to sectorial factors, or to firm-specific factors. The R-squared from regressions on the credit markets risk factors oscillate between 0.21 and 0.57, while the R-squared from regressions on the financial markets risk factors are lower, between 0.05 and 0.27.[12] Taking together both sets of risk factors as explanatory variables, the resulting R-squared provides us with an estimate of the size of systemic risk for each firm, falling between 0.22 and 0.57 and being very close for each firm to those attained by the credit market factors alone. This result shows the difficulty in separating the relevance of credit market factors from that of other financial markets.[13] Hence, we have opted for taking the combined explanatory power of both sets of risk factors as being an estimate of the size of the systemic component of risk.

Column 3 shows the R-squared from a regression from CDS returns on the first principal component estimated for this sector. As in the analysis of sectorial indices in the previous section, the intra-sector first principal component has a higher explanatory power for individual firm CDS returns than the credit and financial risk factors taken together, attaining R-squared values between 0.29 and 0.79. Moreover, when we put together all these factors in column 4, the explanatory power is essentially the same as the one obtained by the principal component alone. Obviously, the principal component combines firm-specific factors with sectorial elements, besides capturing some influence from the global credit market and other financial markets. To distribute the importance of each element, we take in column 5 the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, what remains unexplained by the regression on credit risk factors, financial factors and the sectorial factor (the first principal component for the firms in the sector) can be naturally interpreted as the size of the idiosyncratic component of risk. This way, we have a decomposition of CDS risk in systemic risk (column 2), sector-specific risk (column 5), and firm-specific risk (column 6), adding up to +100%. Firms in Table 3.7, as well as those in the tables for the other sectors, are sorted by the size of their systematic component of risk.

Sectorial risk oscillates between 8% and 28%, while the idiosyncratic component of risk amounts to a percentage between 20% and 69%. In most issuers (27 out of 30), the idiosyncratic component is below 50% of total risk. Bold figures in the table denote the most important component for each single issuer. For 21 of the 30 issuers, credit and financial risk factors are the most important component of CDS risk, while firm-specific factors are the most important component for the other nine issuers. In our estimates, sector-specific components are never the most important source of fluctuations. Attending to median values, the systemic component of risk for the European industrial sector is 44% of total risk, sectorial risk is 20%, and the idiosyncratic component amounts to 35%.[14] In fact, this percent decomposition among the three sources of risk (credit market, sectorial risk and firm-specific risk) would be essentially the same if we just used the credit market risk factors

[12]For reasons of space, these regressions are not shown in the table

[13]If we project each financial risk factor on the set of credit risk factors, to take the residuals from those regressions as the 'pure' influence of financial markets risk factors, their joint explanatory power turns out to minimum. Therefore, even though non-credit risk factors contain information on credit risk for individual issuers, although such information is also contained in credit market risk factors.

[14]Being median values they may not add up exactly to 100%.

as representative of systemic risk, leaving out the information on risk embedded in other financial indicators. We have however included additional credit and interest rate indicators in the estimation of the systemic component of risk to avoid any possible underestimation.

Table 3.7: European industrial issuer CDS spread decomposition

Issuer (1)	Systemic risk (2)	Sector PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
AB Volvo	**57.2%**	73.7%	74.2%	17.0%	25.8%
Cie de St Gobain	**56.9%**	78.4%	78.8%	21.9%	21.2%
Holcim Ltd	**56.7%**	79.3%	79.8%	23.1%	20.2%
Rolls-Royce Plc	**54.9%**	71.0%	73.8%	18.9%	26.2%
Lafarge	**54.7%**	79.1%	79.8%	25.1%	20.2%
Scania Ab	**54.6%**	70.8%	71.4%	16.8%	28.6%
Thales	**52.2%**	77.9%	80.0%	27.8%	20.0%
Finmeccanica S.p.A	**51.7%**	66.5%	68.3%	16.6%	31.7%
Vinci	**51.5%**	73.9%	74.5%	22.9%	25.5%
Volvo Treas AB	**51.0%**	69.2%	70.2%	19.2%	29.8%
Adecco S A	**48.4%**	68.6%	69.1%	20.7%	30.9%
Bae Sys PLC	**48.0%**	71.8%	72.1%	24.1%	27.9%
Deutsche Lufthansa AG	**47.2%**	66.0%	65.8%	18.7%	34.2%
Deutsche Post AG	**44.6%**	58.9%	59.8%	15.2%	40.2%
Eurpn Aero Defence & Space Co Eads N V	**44.5%**	70.3%	70.8%	26.3%	29.2%
Rexam plc	**44.2%**	67.1%	67.0%	22.8%	33.0%
Metso Corp	**43.4%**	62.1%	63.0%	19.6%	37.0%
Heidelberg Cement AG	**42.9%**	58.4%	59.9%	17.0%	40.1%
Societe Air France	**42.1%**	63.8%	63.8%	21.7%	36.3%
Assa Abloy Ab	**41.2%**	62.9%	63.0%	21.8%	37.0%
Alstom	**40.7%**	62.3%	62.1%	21.5%	37.9%
Securitas AB	40.6%	57.4%	59.2%	18.6%	**40.8%**
Siemens AG	39.8%	57.5%	60.1%	20.3%	**39.9%**
Atlas Copco AB	39.3%	59.2%	58.9%	19.6%	**41.1%**
Brit Awys plc	36.4%	53.4%	55.1%	18.7%	**44.9%**
Schneider Elec SA	36.4%	55.8%	55.7%	19.4%	**44.3%**
Smiths Gp Plc	30.2%	51.0%	51.4%	21.2%	**48.6%**
Ab Skf	27.9%	45.2%	45.8%	17.9%	**54.2%**
Rentokil Initial 1927 Plc	23.0%	29.3%	30.9%	7.8%	**69.1%**
Invensys plc	21.8%	37.8%	39.3%	17.5%	**60.8%**

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European industrial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

3.8.2 North American industrial sector

In the North American industrial sector, market power among the 40 issuers is more diluted. The sectorial factor, estimated as the first principal component of CDS spreads across the sector, explains only 44% of the total fluctuation in CDS spreads. This component is again an average of CDS spreads across the industrial sector, excluding a few firms. To capture above 70% of the fluctuation in prices, we would need eight principal components, so there seem to be many specific risk factors.

Simple combinations of the second and third components would single out Crown Holdings, Inc. and PHH Corporation. These two are among the firms that are not represented in the sector average that produces the first principal component. Hence, a linear combination of the second and third principal components would select both firms separately as factors explaining the volatility in the sector. This would be consistent with the possibility that CDS from these two issuers are subject to specific risk factors different from those of other firms. The remaining principal components are again hard to interpret, being linear combinations of CDS spreads with non-uniform weights.

Financial indicators have significant explanatory power for CDS prices by most firms in the sector, leading to a significant estimate of the relevance of systemic risk in the 0.20 to 0.51 range for 31 out of 46 issuers. Somewhat striking is the fact that there are nine issuers for which the regression of CDS returns on the credit and non-credit financial factors have an R-squared lower than 10%.[15,16] A possible explanation might be the low liquidity of these issuers, with repeated price quotes over time and hence a low correlation with market fluctuations. In Table 3.8 we have added one column (7) with information on the gross CDS notional as the sum of CDS contracts bought (or equivalently, sold) for all Warehouse contracts in aggregate for single reference entities. For example, a transaction of $10 million notional between the buyer and seller of protection is reported as one contract and $10 million gross notional, as opposed to two contracts worth $20 million. This information is provided on a weekly basis by DTCC.[17] Figures in that column support the intuition about the lack of liquidity in some issuers for which where there is not available data in the DTCC report, given that the report covers the Top 1000 Reference Entities. Not surprisingly, the most important factor for these issuers without liquidity is the firm-specific factor. A final column (8) reports figures for total assets.

The linear correlation coefficient between the first principal component regression (column 3) and total assets (column 9) for each issuer on 28 December 2012, is 0.52, reflecting the idea that the largest companies are the most systemic ones. This idea has been present in the literature [see, among others, Dietsch and Petey (2002); Dullmann and Scheule (2003); Lopez (2004); and recently, Bams et al. (2012)].

As in the European industrial sector, risk factors from non-credit financial markets do not add explanatory power to the credit market factors. On the contrary, the sectorial first principal component has significant

[15] These are Ball Corp, Briggs & Stratton Corp, Contl Airls Inc, Cooper Inds Ltd, Crown Holdings Inc, JetBlue Awys Corp, PHH Corporation, Rock Tenn Co, and Sonoco Prods Co.

[16] Since our goal is to find a risk model with a reduced number of factors, we feel that just the first principal component should be used as a single factor. If we are interested in explaining the behaviour of CDS prices for Crown Holdings, Inc. and PHH Corporation, then the second and third principal components will also be needed.

[17] Visit http://www.dtcc.com/repository-otc-data.aspx for more details.

explanatory power: except by six firms, R-squared from a simple regression on this principal component is between 0.10 and 0.70. For these six firms for which the sectorial principal component lacks a significant explanatory power, the credit and financial risk factors also produce R-squared values below 10% in column 2, so their credit risk is almost fully idiosyncratic in nature. For 33 out of the 46 firms in the sector, the sectorial first principal component, used by itself as explanatory variable in a regression, produces R-squared coefficients in the 0.30 to 0.74 range. In fact, we have the same situation as in the European industrial sector, with the sectorial first principal component incorporating most of the information content that there is in the credit and financial indicators regarding CDS prices by these issuers, thus the similarity between columns 3 and 4 in the table.

Tables 3.8 and 3.9 reproduce a similar analysis to the one we have run above for the European industrial sector, decomposing the volatility of CDS returns as explained by credit and financial risk factors (systemic risk), sector factors, and firm-specific risk factors. In 15 out of the 46 issuers, the systemic risk factors sector is the most important component of CDS risk. For the remaining 31 sectors, idiosyncratic factors are the most important component of risk. Firm-specific factors are clearly more relevant in the market for CDS from US industrial firms than in the European industrial sector. In thirteen firms, this component accounts for more than 70% of fluctuations in CDS returns, and in 23 firms it accounts for more than 50% of total risk. This result suggests the difficulty in finding a successful hedge for undiversified positions in credit portfolios from these issuers. In terms of median R-squared values across issuers, the credit factor account for 35% of total CDS return risk, the sector factor explains 17%, and firm-specific factors explain the larger amount, 50% of total CDS risk.

Table 3.8: North American industrial issuer CDS spread decomposition

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)	G. Notional (*)(7)	T. Asset (8)
Caterpillar Inc	**51.3%**	73.1%	73.9%	22.6%	26.2%	18,126	89,356
Deere & Co	**48.8%**	69.5%	70.6%	21.8%	29.4%	15,226	56,266
Gen Dynamics Corp	**48.7%**	74.1%	74.0%	25.3%	26.0%	3,016	34,309
Mead Westvaco Corp	**48.4%**	60.7%	63.1%	14.7%	36.9%	20,994	8,908
Boeing Co	**47.7%**	69.0%	70.4%	22.7%	29.6%	6,431	88,896
Arrow Electrs Inc	**46.4%**	60.6%	61.5%	15.2%	38.5%	20,465	10,786
Norfolk Sthn Corp	**43.8%**	66.1%	66.1%	22.3%	33.9%	15,216	30,342
Southwest Airls Co	**43.3%**	59.3%	60.0%	16.6%	40.0%	26,177	18,596
Utd Tech Corp	**42.5%**	73.0%	74.5%	32.1%	25.5%	3,573	89,409
Ryder Sys Inc	**42.4%**	58.3%	59.3%	17.0%	40.7%	15,983	8,319
Emerson Elec Co	**41.3%**	60.6%	61.4%	20.1%	38.6%	2,082	23,818
Bombardier Inc	**40.5%**	63.0%	64.0%	23.5%	36.0%	12,824	25,79
Raytheon Co	**39.7%**	68.1%	68.4%	28.7%	31.7%	12,191	26,686
Lockheed Martin Corp	**39.7%**	65.0%	64.7%	25.0%	35.3%	13,945	38,657
Packaging Corp Amer	**39.6%**	54.5%	55.1%	15.4%	45.0%	5,583	2,454
CSX Corp	**39.5%**	62.5%	62.8%	23.3%	37.2%	15,882	30,571
Sealed Air Corp US	39.1%	49.6%	50.7%	11.6%	**49.3%**	8,95	9,437
Cummins Inc	38.4%	56.4%	56.9%	18.5%	**43.1%**	5,59	12,548
Textron Inc	37.9%	59.6%	59.9%	22.1%	**40.1%**	8,708	13,033
Danaher Corp	37.7%	59.1%	59.5%	21.8%	**40.5%**	4,606	32,941
Eaton Corp	36.9%	54.5%	55.4%	18.5%	**44.6%**	4,338	35,848
FedEx Corp	36.1%	62.3%	62.6%	26.5%	**37.4%**	5,89	29,9
Textron Finl Corp	35.1%	54.3%	55.5%	20.4%	**44.5%**	14,763	13,033

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American industrial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Finally, column (8) reports figures for total asset. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.
(*) Gross notional and total asset in USD millions on 28 December 2012. N/A = Not Available.

Table 3.9: North American industrial issuer CDS spread decomposition (continued)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)	G. Notional (7)	T. Asset (8)
1st Data Corp	34.0%	39.0%	42.6%	8.5%	**57.5%**	22,324	35,24
Cdn Natl Rwy Co	32.2%	48.4%	49.0%	16.9%	**51.0%**	2,114	26,5
Utd Rents Inc	30.1%	43.7%	43.2%	13.1%	**56.8%**	4,613	11,026
Owens IL Inc	27.5%	49.0%	50.0%	22.5%	**50.1%**	3,291	8,598
L 3 Comms Corp	26.4%	49.5%	50.2%	23.8%	**49.8%**	4,508	13,826
R R Donnelley & Sons Co	23.6%	38.1%	38.1%	14.5%	**61.9%**	N/A	7,263
Navistar Intl Corp	23.4%	39.0%	39.1%	15.6%	**60.9%**	N/A	9,102
L 3 Comms Hldgs INC	20.4%	41.9%	44.1%	23.7%	**55.9%**	N/A	13,826
Iron Mtn Inc	19.6%	32.7%	33.5%	14.0%	**66.5%**	3,336	6,358
Waste Mgmt Inc	19.3%	28.1%	29.3%	10.0%	**70.7%**	8,289	23,097
Owens Brockway Glass Container Inc	16.1%	30.3%	33.2%	17.1%	**66.8%**	N/A	8,598
Case New Holland Inc	14.7%	21.2%	21.7%	7.0%	**78.3%**	N/A	48,965
Rd King Infstruc	14.0%	14.8%	15.6%	1.6%	**84.4%**	N/A	N/A
Rep Svcs Inc	13.3%	22.5%	22.2%	8.9%	**77.8%**	4,821	19,617
Contl Airls Inc	8.6%	20.4%	20.7%	12.1%	**79.3%**	N/A	37,628
Cooper Inds Ltd	8.1%	7.9%	12.8%	4.7%	**87.2%**	N/A	35,848
JetBlue Awys Corp	7.1%	15.7%	15.7%	8.7%	**84.3%**	N/A	7,07
Sonoco Prods Co	5.9%	3.9%	7.0%	1.1%	**93.0%**	N/A	4,176
Rock Tenn Co	3.4%	10.3%	12.2%	8.8%	**87.8%**	N/A	10,733
Ball Corp	2.9%	5.2%	5.0%	2.1%	**95.0%**	N/A	7,507
PHH Corp	2.4%	0.5%	2.2%	0.0%	**97.8%**	2,027	9,603
Briggs & Stratton Corp	0.0%	0.8%	0.7%	0.9%	**99.1%**	N/A	1,608
Crown Cork & Seal Co Inc	0.0%	0.0%	0.0%	0.0%	**100.0%**	N/A	7,49

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American industrial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Finally, column (8) reports figures for total asset. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

(*) Gross notional and total asset in USD millions on 28 December 2012. N/A = Not Available.

3.8.3 European financial sector

The BaselCommittee (2012a) identifies five broad categories of factors that influence global systemic importance. The selected indicators reflect the size of banks, their interconnectedness, the lack of readily available substitutes or financial institution infrastructure for the services they provide, their global (cross-jurisdictional) activity and their complexity. Tables 3.10 to 3.12 show an example of the interconnectedness in the European financial sector with a similar decomposition of CDS risk for its issuers. Systemic credit risk factors account for between 4% and 60% of total risk in the firms in this sector and the intra-sector first principal component explains between 7% and 86% of CDS risk. Sectorial risk falls between 0% and 54% and idiosyncratic risk is between 14% and 93%. In terms of median values, systemic risk accounts for 32% of total risk, sectorial risk is 33% and idiosyncratic risk 39% of total risk.

These figures are similar to those shown in the European industrial sector, although in the financial sector the idiosyncratic component is more important. Indeed, in half of the firms (34 out of 70), the idiosyncratic component is the most important. For 19 firms the systemic component is the most important while for 17 firms the sectorial component of risk prevails.[18]

The sectorial risk factor achieves its largest relevance for Dexia. It is clear that the firms more influenced by the credit factors are the largest ones. Lack of liquidity again can be the main reason why so many firms are highly influenced by firm-specific factors.

[18] The fact that the lower bound of the explanatory power of credit risk factors is lower than in the European industrial sector could be explained by the lack of liquidity in some issuers because of the recent financial crisis. That is the case of Bancaja that finally merged into Bankia along with "Caja de Ahorro y Monte de Piedad de Madrid".

Table 3.10: European financial issuer CDS spread decomposition

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
CIE Fin Michelin	**59.7%**	54.2%	67.5%	7.8%	32.6%
Ace Ltd	**47.9%**	36.5%	52.9%	5.0%	47.1%
Axa	**47.5%**	72.4%	75.0%	27.5%	25.0%
Bca Monte dei Paschi di Siena S p A	**46.8%**	79.5%	81.1%	34.4%	18.9%
Assicurazioni Generali S p A	**45.2%**	80.1%	80.6%	35.4%	19.4%
Aviva plc	**44.5%**	73.1%	74.7%	30.2%	25.3%
Bnp Paribas	**44.1%**	84.8%	85.1%	41.0%	14.9%
Bco Bilbao Vizcaya Argentaria S A	**43.5%**	75.7%	77.3%	33.8%	22.7%
Mediobanca SpA	**43.0%**	81.0%	81.1%	38.2%	18.9%
Munich Re	**41.5%**	76.8%	76.9%	35.4%	23.1%
Deutsche Bk AG	**40.5%**	77.6%	77.9%	37.3%	22.1%
Societe Generale	40.2%	82.8%	83.2%	**43.1%**	16.8%
Royal & Sun Alliance Ins PLC	**40.1%**	73.9%	74.1%	34.0%	25.9%
Bca Pop di Milano Soc Coop a r l	**39.8%**	79.3%	79.4%	39.6%	20.7%
Hannover Ruck Ag	**39.7%**	76.4%	76.7%	36.9%	23.3%
Prudential Plc	**39.6%**	68.3%	69.5%	29.9%	30.6%
Raiffeisen Zentralbank Oesterreich Ag	39.0%	55.6%	57.7%	18.6%	**42.4%**
Standard Chartered Plc	**38.8%**	73.8%	74.2%	35.4%	25.8%
Legal & Gen Gp Plc	**38.8%**	70.5%	70.7%	31.9%	29.3%
Old Mut plc	38.8%	45.1%	50.2%	11.4%	**49.9%**
Cr Agricole SA	38.7%	83.4%	83.8%	**45.1%**	16.2%
Ing Bk N V	38.4%	86.2%	86.5%	**48.1%**	13.5%
Hsbc Bk plc	38.3%	81.8%	82.3%	**44.0%**	17.7%

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.11: European financial issuer CDS spread decomposition (continued I)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Rabobank Nederland	38.2%	79.9%	81.4%	**43.2%**	18.6%
Bca Naz del Lavoro S.p.A	37.9%	80.2%	80.0%	**42.0%**	20.0%
Volkswagen Finl Svcs AG	**37.1%**	32.9%	41.3%	4.3%	58.7%
Cr Lyonnais	36.9%	81.7%	82.0%	**45.1%**	18.0%
Std Chartered Bk	36.4%	74.0%	74.1%	**37.6%**	26.0%
Aegon N.V.	36.0%	55.7%	57.6%	21.6%	**42.4%**
Ing Verzekeringen NV	**35.6%**	70.5%	71.0%	35.4%	29.0%
Lloyds Tsb Bk Plc	34.8%	78.9%	80.0%	**45.2%**	20.0%
Cir Intl SA	34.5%	17.9%	34.4%	0.0%	**65.5%**
Ubs AG	33.9%	75.7%	76.3%	**42.4%**	23.7%
Bco Comercial Portugues SA	32.9%	73.0%	73.3%	**40.4%**	26.7%
Barclays Bk plc	32.6%	78.6%	79.3%	**46.6%**	20.8%
Commerzbank AG	32.1%	79.1%	79.9%	**47.8%**	20.1%
Gecina	31.1%	35.5%	39.4%	8.3%	**60.6%**
Skandinaviska Enskilda Banken AB	30.8%	59.3%	59.8%	29.0%	**40.3%**
Hsbc Hldgs plc	30.3%	68.4%	69.1%	**38.9%**	30.9%
Nordea Bk AB	29.9%	56.9%	57.3%	27.4%	**42.7%**
Bco Espirito Santo S A	29.5%	71.4%	72.2%	**42.7%**	27.8%
Royal Bk of Scotland Pub Ltd Co	29.4%	75.2%	76.2%	**46.8%**	23.8%
Danske Bk A S	28.2%	58.7%	61.5%	33.4%	**38.5%**
Inv AB	28.0%	24.3%	30.8%	2.8%	**69.2%**
Hammerson PLC	27.5%	26.6%	32.2%	4.7%	**67.8%**
Kbc Bk	26.7%	58.6%	58.7%	32.0%	**41.3%**

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.12: European financial issuer CDS spread decomposition (continued II)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Iss Glob A S	25.5%	30.1%	33.0%	7.5%	**67.0%**
Klepierre	23.5%	20.1%	25.5%	2.0%	**74.5%**
La C de Aho y Pensiones de Barcelona	21.4%	56.3%	56.9%	35.5%	**43.1%**
Sns Bk NV	20.8%	50.7%	50.7%	30.0%	**49.3%**
Bco de Sabadell S A	20.3%	51.0%	51.9%	31.6%	**48.1%**
Landbk Baden Wuertbg	19.9%	43.3%	45.3%	25.4%	**54.7%**
Bay Landbk Giroz	19.4%	52.9%	55.3%	36.0%	**44.7%**
Alliance & Leicester plc	18.5%	51.1%	51.7%	33.2%	**48.4%**
3i Gp plc	18.0%	21.4%	23.5%	5.5%	**76.5%**
Bqe Federative Du Cr Mutuel	17.6%	41.3%	41.1%	23.5%	**58.9%**
Svenska Handelsbanken AB	17.3%	51.0%	52.3%	35.0%	**47.7%**
Dexia Cr Loc	15.1%	62.1%	69.0%	**53.9%**	31.0%
C de Aho Vlncia Castlln Alicnte Bcaja	15.1%	34.5%	34.5%	19.4%	**65.5%**
C de Aho Y Monte de Piedad de Madrid	13.7%	45.7%	46.9%	33.2%	**53.1%**
DZ Bk AG	12.7%	25.3%	25.4%	12.7%	**74.7%**
Alpha Bk AE	11.3%	27.5%	27.4%	16.1%	**72.6%**
Nationwide Bldg Soc	10.9%	46.3%	51.4%	40.5%	**48.6%**
Landbk Hessen thueringen Giroz	10.5%	23.2%	22.5%	12.1%	**77.5%**
Brit Ld Co plc	9.9%	10.3%	11.6%	1.7%	**88.4%**
Storebrand ASA	9.7%	6.8%	10.0%	0.3%	**90.0%**
Fortis Bk	9.0%	42.0%	47.0%	38.0%	**53.0%**
Ikb Deutsche Industriebank AG	7.8%	23.1%	22.9%	15.1%	**77.1%**
Bawag P.S.K	7.8%	21.6%	22.4%	14.6%	**77.6%**
Ld Secs PLC	4.2%	8.1%	7.0%	2.8%	**93.0%**

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

3.8.4 North American financial sector

In terms of median R-squared values across North American financial issuers, the systemic factor accounts for 33% of total CDS return risk, sectorial factors explain 17%, and firm-specific factors explain the largest amount, 46% of total CDS risk [Tables 3.13 and 3.14]. These figures are very similar to those we obtained for the North American industrial sector. In 41 out of the 61 issuers, firm-specific factors are the most important component of risk, while systemic risk is the second component in importance, with credit and financial market factors being the most important component of risk in 19 out of the 61 firms. In one firm, the sectorial component of risk turned out to be the most important. This result once more suggests the difficulty in finding a successful hedge for undiversified positions in CDS from these issuers, which might possibly be explained by the lack of liquidity of the issuers.

Table 3.13: North American financial issuer CDS spread decomposition

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Berkshire Hathaway Inc	**51.2%**	65.4%	67.1%	15.9%	32.9%
MetLife Inc	**49.7%**	78.0%	78.3%	28.6%	21.7%
Prudential Finl Inc	**47.9%**	74.2%	74.4%	26.5%	25.6%
Hartford Finl Services Group Inc	**47.7%**	76.1%	76.4%	28.7%	23.6%
Gen Elec Cap Corp	**46.4%**	73.2%	73.0%	26.6%	27.0%
Allstate Corp	**46.4%**	64.4%	65.8%	19.4%	34.2%
Simon Ppty Gp L P	**45.1%**	62.6%	63.6%	18.5%	36.4%
Amern Express Co	**44.4%**	77.3%	77.6%	33.1%	22.4%
Boeing Cap Corp	**44.4%**	54.5%	58.8%	14.4%	41.2%
Chubb Corp	**43.6%**	61.0%	63.0%	19.4%	37.0%
Simon Ppty Gp Inc	**43.3%**	59.1%	60.0%	16.6%	40.1%
Caterpillar Finl Svcs Corp	**43.3%**	55.6%	58.4%	15.1%	41.6%
Erp Oper Ltd Pship	**43.2%**	57.6%	58.5%	15.3%	41.5%
Lincoln Natl Corp	**43.1%**	66.8%	66.8%	23.7%	33.2%
Cna Finl Corp	**41.2%**	62.0%	62.5%	21.4%	37.5%
John Deere Cap Corp	41.1%	54.8%	56.6%	15.5%	**43.4%**
Avalon Bay Cmntys Inc	**39.7%**	53.4%	54.0%	14.3%	46.0%
Loews Corp	39.6%	56.4%	56.8%	17.2%	**43.2%**
Liberty Mut Ins Co	39.0%	58.2%	59.3%	20.3%	**40.7%**
Goldman Sachs Gp Inc	**38.8%**	62.2%	62.3%	23.6%	37.7%
Genworth Finl Inc	38.3%	56.3%	56.9%	18.6%	**43.1%**
Hsbc Fin Corp	**37.5%**	67.4%	68.2%	30.8%	31.8%
JPMorgan Chase & Co	**37.1%**	62.9%	63.9%	26.8%	36.1%
Bk of America Corp	36.8%	61.2%	62.7%	25.9%	**37.3%**
Aon Corp	35.6%	49.2%	50.0%	14.5%	**50.0%**
Citigroup Inc	35.3%	61.8%	63.0%	27.7%	**37.0%**
Sears Roebuck Accep Corp	35.2%	31.1%	38.5%	3.3%	**61.5%**
Cap One Finl Corp	35.0%	63.2%	63.6%	28.6%	**36.4%**
Heller Finl Inc	34.4%	55.5%	55.2%	20.8%	**44.9%**
Morgan Stanley	34.3%	61.2%	62.2%	27.9%	**37.8%**
Gatx Corp	33.0%	36.4%	40.9%	7.8%	**59.2%**

Note: Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the sectorial risk. Column 6 displays the size of idiosyncratic risk, as 1.0 minus the adjusted R-squared in column 4.

Table 3.14: North American financial issuer CDS spread decomposition (continued)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Wells Fargo & Co	32.0%	62.9%	63.7%	31.7%	**36.3%**
Marsh & Mclennan Cos Inc	30.5%	37.2%	38.4%	8.0%	**61.6%**
Merrill Lynch & Co Inc	28.4%	55.8%	56.8%	28.4%	**43.2%**
Health Care REIT Inc	27.4%	40.1%	41.0%	13.6%	**59.0%**
Intl Lease Fin Corp	27.3%	64.4%	66.8%	**39.5%**	33.3%
Philip Morris Cap Corp	27.2%	35.6%	36.7%	9.5%	**63.3%**
Mack Cali Rlty LP	26.1%	42.3%	41.8%	15.7%	**58.2%**
Natl Rural Utils Coop Fin Corp	25.7%	50.4%	52.6%	26.9%	**47.4%**
Amern Express Cr Corp	25.4%	44.6%	44.3%	19.0%	**55.7%**
Duke Rlty Ltd Partnership	25.4%	35.2%	35.2%	9.8%	**64.8%**
Istar Finl Inc	24.9%	41.9%	42.9%	18.0%	**57.1%**
MBIA Ins Corp	24.3%	36.7%	36.7%	12.4%	**63.4%**
MGIC Invt Corp	19.6%	43.1%	45.1%	25.5%	**54.9%**
MBIA Inc.	19.6%	32.4%	34.2%	14.6%	**65.8%**
Amern Intl Gp Inc	18.5%	48.1%	53.3%	34.8%	**46.7%**
Radian Gp Inc	18.5%	40.9%	41.6%	23.0%	**58.4%**
EOP Oper Ltd Pship	18.3%	28.2%	27.6%	9.3%	**72.4%**
Radian Asset Assurn Inc	18.0%	40.0%	40.7%	22.7%	**59.3%**
Healthcare Rlty Tr Inc	17.4%	22.9%	23.4%	6.1%	**76.6%**
SLM Corp	16.3%	29.3%	29.5%	13.2%	**70.5%**
Safeco Corp	14.7%	25.8%	27.2%	12.5%	**72.8%**
Odyssey Re Hldgs Corp	12.6%	21.6%	23.9%	11.3%	**76.2%**
Toyota Mtr Cr Corp	12.0%	18.7%	18.3%	6.3%	**81.7%**
Fairfax Finl Hldgs Ltd	11.6%	19.6%	18.9%	7.2%	**81.1%**
Brookfield Asset Mgmt INC	10.8%	7.9%	10.8%	0.0%	**89.2%**
Charles Schwab Corp	9.1%	9.7%	10.5%	1.4%	**89.5%**
Amern Finl Gp Inc	6.2%	13.8%	13.6%	7.4%	**86.4%**
Highwoods Rlty LP	4.3%	5.9%	7.2%	2.9%	**92.8%**
Legg Mason Inc	0.0%	0.4%	0.0%	0.2%	**100.0%**
Franklin Res Inc	0.0%	0.2%	0.0%	0.0%	**100.0%**

Note: Column 2 displays the adjusted R-squared from a regression on two first principal components of credit and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the sectorial risk. Column 6 displays the size of idiosyncratic risk, as 1.0 minus the adjusted R-squared in column 4.

3.8.5 An alternative decomposition of risk

We argued in Section 3.4 that the global risk factor we constructed could also be thought of capturing the systemic elements of risk as an alternative to using financial indicators for that purpose, as we have done in the decompositions above. Hence, an alternative decomposition to the one we have used in the previous paragraphs would estimate the relevance of systemic risk by the adjusted R-squared of CDS spreads for each firm on the global risk factor. The first intra-sector principal component adds some sector-specific information to the global risk factor, and we take the difference between their joint explanatory power and that of the global risk factor alone as an estimate of the relevance of sectorial risk. The residual in that joint regression is an estimate of the idiosyncratic component of risk, its relevance being estimated as 1.0 minus the R-squared in such regression.

Surprisingly enough, estimates of risk components by both procedures are quite similar. With the exception of the sectorial component of risk in North American industrials, correlation coefficients between the estimates obtained by both approaches are very high.

Table 3.15: Linear correlation coefficients between components of risk by both procedures

Sector	Systemic	Sectorial	Idiosyncratic
European industrial	93%	78%	99%
North American industrial	86%	34%	99%
European financial	92%	94%	99%
North American financial	92%	84%	93%

Note: Linear correlation between systemic, sectorial and idiosyncratic components of risk obtained by both procedures. The first procedure uses principal components for financial indicators to characterize systemic risk, as in Tables 3.7, 3.8, 3.9, 3.10, 3.11, 3.12, 3.13 and 3.14. The alternative procedure uses the global risk factor to characterize systemic risk.

Median values are also quite similar, with systemic risk being somewhat higher and sectorial risk lower when the global risk factor is used to estimate systemic risk. The fact that the sectorial component of risk is higher for the European financial sector may be due to the depth of the crisis experienced by this sector. The decompositions of risk for the four sectors analysed above can be found in the Appendix 3.11.

Table 3.16: Median values of risk components estimated by two alternative decomposition procedures

Sector		Systemic	Sectorial	Idiosyncratic
European industrial	Indicators	35%	17%	50%
	Global risk factor	38%	11%	51%
North American industrial	Indicators	44%	20%	35%
	Global risk factor	55%	10%	35%
European financial	Indicators	32%	33%	39%
	Global risk factor	41%	20%	44%
North American financial	Indicators	33%	17%	46%
	Global risk factor	38%	11%	44%

3.8.6 An effective separation of the sectorial and idiosyncratic components of risk

The estimated idiosyncratic component of CDS risk turns out to be quite large in many firms, especially in the US market. Another interpretation might be that the large size of our estimated idiosyncratic component might be due to still containing some systemic risk elements. To check on the effectiveness of our methodology to identify the idiosyncratic component of credit risk we discuss now two related issues.

The first issue is whether our estimated sectorial component of risk to see whether it is free from idiosyncratic features. CDS spreads for North American financial issuers have a median pairwise linear correlation coefficient of 0.45, while the median correlation between each firm in the sector and the Financial Sector Credit Index in Section 3.4 is 0.67, with a highest correlation of 0.79. Thus, North American financial firms share important elements of risk and they bear a relatively close association with the Sectorial Credit Index, showing that there exists a well-defined sectorial component of risk.

The intra-sector first principal component for these firms has a still higher correlation, of 0.90, with the Credit Index for the financial sector. Such correlation is unexpectedly high. The Financial Sector Credit Index defined in Section 3.4 is made up by the median spread negotiated each day in CDS by all issuers in the financial sector from all the different geographical regions. Therefore, each daily observation on the Financial Sector Credit Index may come from a different financial firm, and even from a different country. On the other hand, the principal component for the North American financial sector is a linear combination of spreads from all CDS traded each day by North American issuers. It is, hence, some sort of average of these specific CDS, all of them from the same geographical area. The two measures are different enough so that such a high correlation between them is far from obvious. Such high correlation shows that the average of CDS spreads that is embedded into the intra-sector principal component is successful at filtering out idiosyncratic components, essentially capturing the same sectorial features as the Credit Index for the global financial sector.

Strikingly enough, the European financial sector shares these characteristics: the correlation between our estimate of the sectorial component of risk and the Financial Credit Index from Section 3.4 is again 0.90.[19] Individual CDS spreads have moderately high correlations between them, with a median value of 0.54, and a median correlation of 0.71 with the Financial Credit Index, with a maximum of 0.84. Again, the estimated sectorial component of risk is much closer to the sectorial credit index than CDS spreads for individual firms, showing that the former is quite free from idiosyncratic features.

Results for industrial sectors are also similar. The estimated sectorial component of risk from industrial firms' CDS data is highly correlated with the Industrial Sector Credit Index from Section 3.4. That correlation is 0.78 for North American firms and 0.85 for European issuers. Correlations between firms in these sectors are again relatively high, with median values of 0.41 and 0.62. As to correlations between individual firms and the sectorial risk factor, median values are 0.56 and 0.71, respectively, with maximum levels of 0.67 and 0.77. Again, the sectorial component of risk of the two industrial sectors has a closer co-movement with the Industrial Credit Index than individual firms in the sector, with the same interpretation as in the case of the financial sectors.

[19] Incidentally, remember that the Financial Sector Credit Index is the same for European and North American firms.

The bottom line of this analysis is that we can indeed use the principal component methodology with data from a given geographical region to extract a sectorial component of risk that turns out to be very similar to the sectorial credit index that can be obtained from all CDS trading in all regions. Our construction of the global sector factor is not directly responsible for this result. In fact, choosing the median of all CDS spreads traded each day over the world does not seem to be the more direct way to generate a high correlation with an average of sector spreads in a specific region. The implications are important. They suggest that the first intra-sector principal component across firms is essentially free of firm idiosyncratic characteristics, thereby justifying our estimates of sectorial components of risk. It also suggests that the sectorial component of risk is more important than its geographical component, as we will examine in the next section.

The second issue relates to whether our estimates of the idiosyncratic components of risk have the appropriate features. First of all, our estimates of the idiosyncratic components of risk turn out to be essentially uncorrelated across firms, which is a necessary condition for the interpretation we give to this component. There are 30 issuers in the European industrial sector, 46 in the North American industrial sector, 70 in the European financial sector, and 61 issuers in the North American financial sector. That amounts to 435 and 1035 correlations between pairs of idiosyncratic components in the European and North American industrial sectors and 2415 and 1830 correlations in the European and North American financial sectors. Median correlations are very low: -0.05, -0.02, -0.02 and -0.02. Ninety per cent of them are in absolute value below 0.23, 0.19, 0.24 and 0.27, respectively. These are all low levels that justify an interpretation of our estimated idiosyncratic components as being firm-specific in nature.

A further check on the nature of our estimated idiosyncratic components consists of examining the possibility of diversification. If idiosyncratic components are relatively important, then a well-diversified portfolio should be much easier to hedge than positions on individual assets. In the European industrial sector, hedging positions on CDS from an individual firm using a contrary position on iTraxx leads to a reduction in variance, as obtained by comparing the variance of residuals from a regression of single firm issuer CDS returns on weekly changes in iTraxx. The estimated slope coefficient would determine the size of the position to be taken in iTraxx. Table 3.17 shows the reduction in variance achieved by hedging individual CDS with a contrary position in the iTraxx Index. Median and maximum values for variance reduction in each sector are shown. Column 4 shows the reduction in variance from hedging the equally weighted portfolio. In the four sectors, hedging the equally weighted portfolio is much more successful than hedging a position in any single firm in the sector, suggesting that we have sensible estimates of idiosyncratic components of risk.

Furthermore, the hedging possibilities change with the size of the idiosyncratic component of risk, as it should be expected. The lower panel in Table 3.17 displays the reduction in variance from hedging the portfolios made up by the five or ten firms with the higher (first column) or lower (second column) idiosyncratic components of risk. Hedging efficiency is clearly higher for portfolios made up by firms with high idiosyncratic risk. Among portfolios with low idiosyncratic risk, it seems easier to hedge portfolios including a larger number of firms.

Table 3.17: The idiosyncratic component of risk as a guide for hedging

Sector	Single CDS		Equally weighted portfolio
	Median	Maximum	
European industrial	14.1%	23.6%	30.0%
North American industrial	24.7%	33.5%	41.0%
European financial	20.0%	35.0%	36.2%
North American financial	15.6%	27.4%	33.3%

Sector		Higher idiosyncratic component	Lower idiosyncratic component
European industrial	5-firm	62%	43%
	10-firm	65%	54%
North American industrial	5-firm	48%	3%
	10-firm	50%	13%
European financial	5-firm	56%	24%
	10-firm	59%	35%
North American financial	5-firm	49%	7%
	10-firm	50%	21%

Note: The upper panel (columns 2 and 3) shows the reduction in variance achieved by hedging individual CDS with a contrary position in the iTraxx Index. Median and maximum values for variance reduction in each sector are shown. Column 4 shows the reduction in variance from hedging the equally weighted portfolio. The lower panel displays the reduction in variance from hedging the portfolios made up by the five or ten firms with the higher (column 3) or lower (column 4) idiosyncratic components of risk.

The low correlation among them and the good possibilities for hedging risk of a well-diversified sectorial portfolio suggest that our estimates of the idiosyncratic components of risk are appropriate.

But then, what is behind the large idiosyncratic component of risk? A possible conjecture for the large size of idiosyncratic components of risk might be, again, that they are just a reflection of the low liquidity in some issues. To check on this assumption, we could try to relate the size of the estimated idiosyncratic risk with either the number of contributors giving price to the 5-year CDS (Composite depth 5yr.), the quality rating of the data provided by Markit, or the volatility of CDS returns. In the latter case, the argument would be that illiquid CDS would often repeat price in the Markit Quotes, with the time series of CDS spreads then having a relatively low variance. Hence, we would expect a negative correlation between the size of the idiosyncratic component of risk and the volatility of CDS spreads. The correlation between the size of the idiosyncratic risk component and the annual volatility of CDS returns among European industrial issuers is equal to -0.30, being equal to -0.03 for North American industrial issuers. That correlation is equal to -0.60 for European financial issuers, and -0.46 for North American financial issuers. Hence, there seems to be, in fact, some evidence on the fact that the large size of the idiosyncratic risk component for some issuers is in part due to the low liquidity of their CDS.

3.9 Some considerations about CDS risk premia

We formulated in the Introduction several questions related to the implications of our main goal of estimating the decomposition of risk we have just described. We answer them in this section using the results we have obtained in the preceding sections.

- What were the most systemic sectors during 2006-2012?

Throughout the paper, we have interpreted the first principal component calculated over the sectorial credit indices as a global risk factor. This is justified by the results we have presented as well as by the analysis in Peña and Rodriguez-Moreno. Then Table 3.3 shows that the most systemic sector was the financial sector. The first principal component has an R-squared above 80% when explaining the variation of the Financial Sector Index for the whole period 2006-2012. These results are consistent with Moody's [Munves (2008)] and the Basel Committee (2011), where the Basel Committee proposed an specific increase in the estimated value of asset correlation for the financial sector when calculating the level of regulatory capital required. That correlation was set at 30%, up from the previous value of 24%, while the 24% correlation was kept for the rest of corporate sectors. According to our methodology, the industrial sector was the second most systemic sector during this period of time, possibly reflecting the impact of the global financial crisis in the real economy, since the industrial sector is distinctively dependent on financing and capital for their long-run investments, as well as reflecting the impact of the increased deterioration in the global housing market.

- What were the sectors with the largest idiosyncratic component of risk during 2006-2012?

Along the same line of reasoning, the two sectors that are less correlated with the rest of the sectors have been the health care sector and the technology sector. That would make harder to hedge credit portfolios in these sectors by taking contrary positions in some others. This outcome is not surprising, taking into account the robust growth that the health care sector is experiencing around the world. This is especially the case in the developed countries (which represent the major part of our data sample) as the population of these countries is getting older, with more economic resources and a greater demand for health care services so as to achieve a better quality of life. As a consequence, the health care sector has been less influenced by the recent crisis. On the other hand, CDS returns in the technology sector have also shown low correlations with the rest of the market, possibly because of the specific nature of innovation in this industry, which has a life cycle very different from the other sectors of the economy.

- What are the most influential financial variables explaining credit spread fluctuations?

There are alternative sets of explanatory factors that can be used to explain a very significant percentage of the time fluctuations in our estimated global risk factor. This is interesting because, as we have repeatedly pointed out, such factor represents the general evolution in the CDS spreads market. Interest rates, like the overnight LIBOR rate or its spread with the EONIA rate, the 3-month EURIBOR rate, the US Treasury 5-year rate, the slope and curvature of the term structure of US swap rates, are correlated negatively with CDS spreads. In particular, the negative correlation between CDS premia and the risk-free rate rate is similar to the result documented for bond yield spreads by Longstaff and Schwartz (1995) and also by Ericsson et al. (2009) when analysing the single-name CDS. This is an important result for the estimation of wrong-way risk, since a standard assumption is to consider independence between interest rates and CDS when searching for indicators of the risk exposure of derivatives, which might lead to an underestimation of the level of risk. Another interesting empirical result is the observed positive correlation between volatility indicators like VIX, the implied volatility of the euro/dollar exchange rate, US swaption rates, and the global risk factor for the CDS market, which could be used for hedging purposes.[20] This represents an interesting open question that would require further research.

- How is the risk of CDS spreads decomposed among systemic risk, sector risk and idiosyncratic risk?

We have analysed industrial and financial sectors in Europe and North America to find that, in terms of median R-squared values across issuers:

(SEE TABLE 3.16)

These results suggest the high risk involved in undiversified positions in CDS from issuers in these sectors, especially in the illiquid CDS market circumstances that arose with the financial crisis, which still exist today. They are also interesting for pricing reasons, since we could use this information to infer the credit premium of a new issuer. On the other hand, to the extent that the idiosyncratic components of risk could be uncorrelated, they might allow for interesting hedging strategies, which we comment next.

- Can the use of credit indices hedge a diversified CDS portfolio appropriately?

The answer is yes. In the light of the results of our analysis, the global risk factor displays high and positive correlations with the iTraxx, in consistency with the interpretation we have given to the factor. A simple regression of CDS sectorial indices with iTraxx as the only explanatory variable, other than a constant term, leads to beta estimates between 0.35 and 0.50, and R-squared coefficients between 0.20 and 0.50. An ex-post analysis of a delta-hedging strategy for a sectorial credit portfolio based on using the estimated beta to define a contrary position in the iTraxx Index, shows a substantial reduction of about 70% or higher in return variance, except for the health care and technology sectors.

Furthermore, we have also shown in previous sections that the low correlation of idiosyncratic components allows for a diversified credit portfolio in either one of the four sectors considered, that can be hedged following a delta-hedge strategy with the iTraxx Index. In fact, portfolios made up by firms with higher idiosyncratic component allow for quite an efficient hedge through contrary positions on the iTraxx Index, while portfolios made up by firms with lower idiosyncratic component are much harder to hedge, as expected.

These results reinforce the appropriateness of our estimates of idiosyncratic risk. They also suggest the interest of running a more detailed, ex-ante examination of the efficiency of a hedge strategy designed with the conditional second order moments estimated from a GARCH specification, possibly with some asymmetric (leverage) effects on volatility, which we leave as an issue for future research.

[20] The global risk factor shows also a natural positive association with credit indices and implicit volatility indicators for credit markets.

- Is there a strong geographical factor in the intra-sector analysis of the different corporate sectors?

A further implication from the result in the previous paragraph is that the first principal components for a given sector, estimated in different geographical regions, display similar fluctuations over time, since they are all highly correlated with the sectorial factor from Section 3.4. This suggests that the sectorial factor is more important to determine CDS spreads than the geographical region. It also implies that it might be more promising to hedge a credit position taking contrary positions in the same sector in other regions than in different sectors from the same region. In fact, the sectorial risk factors for the industrial sectors in the US and Europe display a high correlation of 0.85, suggesting that sector-specific risk factors have a strong global nature, capturing elements of risk that are common to different geographical areas.

A similar observation emerges from the comparison between estimates of the sectorial components of risk for the financial sectors in Europe and North America, which are again closely related. The implication is that the sectorial factor may be much more important than the geographical factor, suggesting that firms should be thought of as members of a global sector instead of members of a particular region, there not being a noticeable diversification across the geographies in the corporate sectors. This kind of result should be interesting for financial institutions when establishing an adequate asset allocation policy for the corporate market. It seems that sectorial factors are more determinant than the geographical factors in the corporate market under normal market circumstances (for example, during a specific crisis in a country, the geographical factor is going to be decisive in the CDS of those issuers within that country). However, we should not forget that the geographical factors are more decisive for small/medium enterprises and for retail banking.

3.10 Conclusions

Whether or not the failure of a single firm evolves into a systemic crisis depends on the relevance of each firm in a given sector, as well as on the relevance of each sector in the global economy. In this paper we have advanced a decomposition of credit risk at the level of individual firms among systemic, sectorial and idiosyncratic components. At the level of sectors we have decomposed risk into a systemic and an idiosyncratic component.

We have started by estimating a global risk factor, and analysing its relationship with a wide array of credit and non-credit financial indicators. The information provided by this analysis has helped us to implement the risk decompositions mentioned above. We have identified the financial sector as being the more systemic, followed by the industrial sector. Health care and technology are the sectors displaying a higher idiosyncratic component of risk and hence, a lower correlation with all the others. We have shown that well-diversified credit portfolios with CDS from a given sector have good possibilities for hedging by taking a contrary position in iTraxx or CDX Indices or their derivatives. Our decomposition of risk for the industrial and financial sectors points to relatively large idiosyncratic components of risk that are still larger in North American than in European firms, and we have shown some evidence that it is in part due to lack of liquidity. Finally, we have shown clear evidence suggesting that the sectorial component of risk is more important than its geographical component.

Our analysis provides an element for a risk appetite framework at financial institutions, since they could easily use the numerical estimates of risk components we propose to maintain their risk limits when taking their asset allocation decisions. Indeed, we have shown evidence suggesting that portfolios made up by firms with higher idiosyncratic components are easier to hedge, contrary to what happens with portfolios made up by firms with lower idiosyncratic risk components. This is observed uniformly over the four sectors considered. Furthermore, by evaluating the firms and sectors with the most potential to produce systemic risk problems, our analysis should also be considered to be crucial for supervisors and regulators. Even though we restrict our analysis to CDS issuers, further research should attempt to relate our estimated risk components to firms' characteristics such as size of assets and liabilities, profit and loss results, equity and bond prices and market share. That would allow for extending the evaluation of credit risk components for CDS issuers to any other firm, even if it is not a CDS issuer.

3.11 Appendix

Table 3.18: European industrial issuer CDS spread decomposition using GRF as the systemic explanatory variable

Issuer (1)	Systemic risk (2)	Sector PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
AB Volvo	**59.6%**	73.7%	73.7%	14.1%	26.3%
Cie de St Gobain	**66.0%**	78.4%	78.3%	12.3%	21.7%
Holcim Ltd	**65.2%**	79.3%	79.2%	14.1%	20.8%
Rolls-Royce Plc	**52.6%**	71.0%	72.1%	19.5%	27.9%
Lafarge	**67.7%**	79.1%	79.1%	11.4%	20.9%
Scania Ab	**60.7%**	70.8%	70.8%	10.1%	29.3%
THALES	**62.9%**	77.9%	78.0%	15.0%	22.1%
Finmeccanica S.p.A	**52.6%**	66.5%	66.7%	14.1%	33.3%
Vinci	**59.5%**	73.9%	74.0%	14.5%	26.0%
Volvo Treas AB	**58.7%**	69.2%	69.1%	10.4%	30.9%
Adecco S A	**58.9%**	68.6%	68.6%	9.7%	31.4%
Bae Sys PLC	**57.0%**	71.8%	71.9%	14.9%	28.1%
Deutsche Lufthansa AG	**53.3%**	66.0%	66.0%	12.7%	34.0%
Deutsche Post AG	**48.7%**	58.9%	58.8%	10.1%	41.2%
Eurpn Aero Defence & Space Co Eads N V	**57.1%**	70.3%	70.3%	13.2%	29.7%
Rexam plc	**58.7%**	67.1%	67.2%	8.5%	32.8%
Metso Corp	**56.5%**	62.1%	62.6%	6.2%	37.4%
HeidelbergCement AG	**46.7%**	58.4%	58.4%	11.7%	41.6%
Societe Air France	**53.8%**	63.8%	63.7%	9.8%	36.3%
Assa Abloy Ab	**59.2%**	62.9%	64.0%	4.8%	36.0%
Alstom	**51.6%**	62.3%	62.2%	10.6%	37.8%
Securitas AB	**49.0%**	57.4%	57.3%	8.4%	**42.7%**
Siemens AG	**53.5%**	57.5%	58.3%	4.8%	41.7%
Atlas Copco AB	**58.2%**	59.2%	61.3%	3.1%	38.7%
Brit Awys plc	**47.6%**	53.4%	53.6%	5.9%	46.4%
Schneider Elec SA	**50.0%**	55.8%	56.1%	6.1%	43.9%
Smiths Gp Plc	41.3%	51.0%	51.0%	9.7%	**49.0%**
Ab Skf	45.3%	45.2%	47.2%	1.8%	**52.8%**
Rentokil Initial 1927 Plc	24.1%	29.3%	29.1%	5.1%	**70.9%**
Invensys plc	29.1%	37.8%	37.9%	8.8%	**62.1%**

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable.
Column 3 shows the adjusted R-squared from a regression on the first principal component for the European industrial issuers contained in the sample. Column 4 shows the adjusted R-squared
from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.19: North American industrial issuer CDS spread decomposition using GRF as the systemic explanatory variable

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)	G. Notional (*)(7)	T. Asset (8)
Caterpillar Inc	**50.8%**	73.1%	73.3%	22.5%	26.7%	18,126	89,356
Deere & Co	**48.0%**	69.5%	69.7%	21.7%	30.3%	15,226	56,266
Gen Dynamics Corp	**49.4%**	74.1%	74.6%	25.2%	25.4%	3,016	34,309
MeadWestvaco Corp	**43.1%**	60.7%	60.7%	17.6%	39.3%	20,994	8,908
Boeing Co	**50.0%**	69.0%	69.0%	19.0%	31.0%	6,431	88,896
Arrow Electrs Inc	**46.3%**	60.6%	60.5%	14.2%	39.5%	20,465	10,786
Norfolk Sthn Corp	**39.2%**	66.1%	68.4%	29.2%	31.6%	15,216	30,342
Southwest Airls Co	**40.5%**	59.3%	59.5%	19.0%	40.5%	26,177	18,596
Utd Tech Corp	**54.4%**	73.0%	72.9%	18.5%	27.1%	3,573	89,409
Ryder Sys Inc	**45.2%**	58.3%	58.2%	13.1%	41.8%	15,983	8,319
Emerson Elec Co	**47.8%**	60.6%	60.6%	12.8%	39.4%	2,082	23,818
Bombardier Inc	**49.8%**	63.0%	63.1%	13.3%	36.9%	12,824	25,79
Raytheon Co	**41.8%**	68.1%	69.7%	27.9%	30.3%	12,191	26,686
Lockheed Martin Corp	**40.4%**	65.0%	66.4%	26.0%	33.7%	13,945	38,657
Packaging Corp Amer	**45.4%**	54.5%	54.9%	9.5%	45.1%	5,583	2,454
CSX Corp	**36.7%**	62.5%	64.7%	28.0%	35.3%	15,882	30,571
Sealed Air Corp US	35.6%	49.6%	49.5%	13.9%	**50.5%**	8,95	9,437
Cummins Inc	**48.9%**	56.4%	57.3%	8.4%	42.7%	5,59	12,548
Textron Inc	**47.4%**	59.6%	59.7%	12.3%	40.3%	8,708	13,033
Danaher Corp	**47.9%**	59.1%	59.3%	11.5%	40.7%	4,606	32,941
Eaton Corp	**51.3%**	54.5%	56.8%	5.5%	43.2%	4,338	35,848
FedEx Corp	**38.9%**	62.3%	63.5%	24.6%	36.5%	5,89	29,9
Textron Finl Corp	**48.7%**	54.3%	55.7%	7.0%	44.3%	14,763	13,033

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American industrial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Finally, column (8) reports figures for total asset. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.
(*) Gross notional and total asset in USD millions on 28 December 2012. N/A = Not Available.

Table 3.20: North American industrial issuer CDS spread decomposition using GRF as the systemic explanatory variable (continued)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)	G. Notional (7)	T. Asset (8)
1st Data Corp	24.8%	39.0%	39.5%	14.7%	**60.5%**	22,324	35,24
Cdn Natl Rwy Co	36.7%	48.4%	48.3%	11.6%	**51.8%**	2,114	26,5
Utd Rents Inc	37.2%	43.7%	44.1%	6.9%	**55.9%**	4,613	11,026
Owens IL Inc	41.0%	49.0%	49.4%	8.4%	**50.6%**	3,291	8,598
L 3 Comms Corp	36.1%	49.5%	49.4%	13.3%	**50.6%**	4,508	13,826
R R Donnelley & Sons Co	27.4%	38.1%	38.0%	10.6%	**62.0%**	N/A	7,263
Navistar Intl Corp	41.2%	39.0%	43.0%	1.8%	**57.0%**	N/A	9,102
L 3 Comms Hldgs INC	30.8%	41.9%	41.8%	11.0%	**58.2%**	N/A	13,826
Iron Mtn Inc	27.6%	32.7%	32.9%	5.3%	**67.1%**	3,336	6,358
Waste Mgmt Inc	25.6%	28.1%	28.8%	3.3%	**71.2%**	8,289	23,097
Owens Brockway Glass Container Inc	24.9%	30.3%	30.4%	5.4%	**69.6%**	N/A	8,598
Case New Holland Inc	25.9%	21.2%	25.8%	0.0%	**74.2%**	N/A	48,965
Rd King Infstruc	25.2%	14.8%	25.9%	0.7%	**74.1%**	N/A	N/A
Rep Svcs Inc	19.8%	22.5%	22.8%	3.0%	**77.2%**	4,821	19,617
Contl Airls Inc	14.0%	20.4%	20.3%	6.4%	**79.7%**	N/A	37,628
Cooper Inds Ltd	7.6%	7.9%	8.0%	0.5%	**92.0%**	N/A	35,848
JetBlue Awys Corp	11.7%	15.7%	15.5%	3.8%	**84.5%**	N/A	7,07
Sonoco Prods Co	6.8%	3.9%	6.7%	0.0%	**93.3%**	N/A	4,176
Rock Tenn Co	8.8%	10.3%	10.2%	1.4%	**89.8%**	N/A	10,733
Ball Corp	8.8%	5.2%	8.9%	0.0%	**91.2%**	N/A	7,507
PHH Corp	1.3%	0.5%	1.2%	0.0%	**98.8%**	2,027	9,603
Briggs & Stratton Corp	2.1%	0.8%	2.2%	0.1%	**97.8%**	N/A	1,608
Crown Cork & Seal Co Inc	0.1%	0.0%	0.5%	0.4%	**99.5%**	N/A	7,49

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American industrial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Finally, column (8) reports figures for total asset. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.
(*) Gross notional and total asset in USD millions on 28 December 2012. N/A = Not Available.

Table 3.21: European financial issuer CDS spread decomposition using GRF as the systemic explanatory variable

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
CIE Fin Michelin	**59.7%**	54.2%	67.5%	7.8%	32.6%
Ace Ltd	**47.9%**	36.5%	52.9%	5.0%	47.1%
Axa	**47.5%**	72.4%	75.0%	27.5%	25.0%
Bca Monte dei Paschi di Siena S p A	**46.8%**	79.5%	81.1%	34.4%	18.9%
Assicurazioni Generali S p A	**45.2%**	80.1%	80.6%	35.4%	19.4%
Aviva plc	**44.5%**	73.1%	74.7%	30.2%	25.3%
Bnp Paribas	**44.1%**	84.8%	85.1%	41.0%	14.9%
Bco Bilbao Vizcaya Argentaria S A	**43.5%**	75.7%	77.3%	33.8%	22.7%
Mediobanca SpA	**43.0%**	81.0%	81.1%	38.2%	18.9%
Munich Re	**41.5%**	76.8%	76.9%	35.4%	23.1%
Deutsche Bk AG	**40.5%**	77.6%	77.9%	37.3%	22.1%
Societe Generale	**40.2%**	82.8%	83.2%	43.1%	16.8%
Royal & Sun Alliance Ins PLC	**40.1%**	73.9%	74.1%	34.0%	25.9%
Bca Pop di Milano Soc Coop a r l	**39.8%**	79.3%	79.4%	39.6%	20.7%
Hannover Ruck Ag	**39.7%**	76.4%	76.7%	36.9%	23.3%
Prudential Plc	**39.6%**	68.3%	69.5%	29.9%	30.6%
Raiffeisen Zentralbank Oesterreich Ag	**39.0%**	55.6%	57.7%	18.6%	42.4%
Standard Chartered Plc	**38.8%**	73.8%	74.2%	35.4%	25.8%
Legal & Gen Gp Plc	**38.8%**	70.5%	70.7%	31.9%	29.3%
Old Mut plc	38.8%	45.1%	50.2%	11.4%	**49.9%**
Cr Agricole SA	38.7%	83.4%	83.8%	**45.1%**	16.2%
Ing Bk N V	38.4%	86.2%	86.5%	**48.1%**	13.5%
Hsbc Bk plc	38.3%	81.8%	82.3%	**44.0%**	17.7%

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.22: European financial issuer CDS spread decomposition using GRF as the systemic explanatory variable (continued I)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Rabobank Nederland	**52.0%**	79.9%	79.9%	27.9%	20.1%
Bca Naz del Lavoro S.p.A	**47.4%**	80.2%	80.4%	32.9%	**19.7%**
Volkswagen Finl Svcs AG	**40.5%**	32.9%	41.5%	1.0%	58.5%
Cr Lyonnais	**42.6%**	81.7%	83.1%	40.4%	16.9%
Std Chartered Bk	**46.6%**	74.0%	73.9%	27.3%	26.1%
Aegon N.V.	**43.3%**	55.7%	56.6%	13.3%	**43.4%**
Ing Verzekeringen NV	**53.9%**	70.5%	71.4%	17.5%	28.6%
Lloyds Tsb Bk Plc	**42.1%**	78.9%	80.0%	37.9%	20.0%
Cir Intl SA	34.5%	17.9%	35.0%	0.4%	**65.0%**
Ubs AG	**42.9%**	75.7%	76.1%	33.2%	23.9%
Bco Comercial Portugues SA	**38.1%**	73.0%	74.3%	36.2%	25.7%
Barclays Bk plc	37.4%	78.6%	81.4%	**44.0%**	18.6%
Commerzbank AG	40.0%	79.1%	81.0%	**41.0%**	19.0%
Gecina	34.9%	35.5%	38.9%	4.0%	**61.1%**
Skandinaviska Enskilda Banken AB	**43.4%**	59.3%	59.7%	16.3%	40.3%
Hsbc Hldgs plc	**41.3%**	68.4%	68.4%	27.1%	31.6%
Nordea Bk AB	39.0%	56.9%	56.9%	17.9%	**43.1%**
Bco Espirito Santo S A	33.7%	71.4%	74.0%	**40.3%**	26.0%
Royal Bk of Scotland Pub Ltd Co	35.6%	75.2%	77.8%	**42.2%**	22.2%
Danske Bk A S	39.7%	58.7%	58.7%	19.0%	**41.3%**
Inv AB	43.4%	24.3%	43.6%	0.2%	**56.4%**
Hammerson PLC	41.8%	26.6%	41.6%	0.0%	**58.4%**
Kbc Bk	40.2%	58.6%	58.6%	18.4%	**41.4%**

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.23: European financial issuer CDS spread decomposition using GRF as the systemic explanatory variable (continued II)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Iss Glob A S	35.6%	30.1%	36.8%	1.2%	**63.2%**
Klepierre	35.5%	20.1%	35.6%	0.1%	**64.4%**
La C de Aho y Pensiones de Barcelona	33.0%	56.3%	56.4%	23.4%	**43.6%**
Sns Bk NV	39.8%	50.7%	51.6%	11.8%	**48.4%**
Bco de Sabadell S A	29.7%	51.0%	51.1%	21.4%	**49.0%**
Landbk Baden Wuertbg	27.0%	43.3%	43.1%	16.2%	**56.9%**
Bay Landbk Giroz	27.8%	52.9%	53.7%	25.9%	**46.3%**
Alliance & Leicester plc	31.3%	51.1%	51.0%	19.7%	**49.0%**
3i Gp plc	35.0%	21.4%	34.9%	-0.1%	**65.1%**
Bqe Federative Du Cr Mutuel	31.3%	41.3%	41.6%	10.4%	**58.4%**
Svenska Handelsbanken AB	31.5%	51.0%	50.9%	19.5%	**49.1%**
Dexia Cr Loc	26.1%	34.5%	34.7%	8.7%	**65.3%**
C de Aho Vlncia Castlln Alicnte Bcaja	28.9%	62.1%	64.5%	35.6%	**35.5%**
C de Aho Y Monte de Piedad de Madrid	25.6%	45.7%	45.9%	20.3%	**54.1%**
DZ Bk AG	22.3%	25.3%	26.5%	4.2%	**73.5%**
Alpha Bk AE	21.4%	27.5%	27.8%	6.5%	**72.2%**
Nationwide Bldg Soc	23.1%	46.3%	47.3%	24.2%	**52.7%**
Landbk Hessen thueringen Giroz	17.2%	23.2%	23.2%	6.0%	**76.8%**
Brit Ld Co plc	21.7%	10.3%	22.2%	0.5%	**77.8%**
Storebrand ASA	9.6%	6.8%	9.4%	0.0%	**90.6%**
Fortis Bk	17.8%	42.0%	44.5%	26.8%	**55.5%**
Ikb Deutsche Industriebank AG	15.3%	23.1%	22.9%	7.6%	**77.2%**
Bawag P.S.K	12.8%	21.6%	21.4%	8.5%	**78.6%**
Ld Secs PLC	11.8%	8.1%	11.6%	0.0%	**88.4%**

Note: Colum1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the European financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, Column 6 displays the size of idiosyncratic risk, computed as 1.0 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor the risk decomposition for each CDS issuer.

Table 3.24: North American financial issuer CDS spread decomposition using GRF as the systemic explanatory variable

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Berkshire Hathaway Inc	**54.9%**	65.4%	66.2%	11.3%	33.8%
MetLife Inc	**54.1%**	78.0%	78.1%	24.0%	22.0%
Prudential Finl Inc	**54.2%**	74.2%	74.1%	19.9%	25.9%
Hartford Finl Services Group Inc	**54.4%**	76.1%	76.0%	21.7%	24.0%
Gen Elec Cap Corp	**53.6%**	73.2%	73.1%	19.5%	26.9%
Allstate Corp	**50.0%**	64.4%	64.4%	14.5%	35.6%
Simon Ppty Gp L P	**60.1%**	62.6%	66.2%	6.1%	33.9%
Amern Express Co	**54.3%**	77.3%	77.4%	23.0%	22.7%
Boeing Cap Corp	**50.6%**	54.5%	56.8%	6.2%	43.2%
Chubb Corp	**47.2%**	61.0%	61.1%	13.9%	38.9%
Simon Ppty Gp Inc	**58.6%**	59.1%	63.4%	4.8%	36.6%
Caterpillar Finl Svcs Corp	**53.5%**	55.6%	58.8%	5.3%	41.2%
Erp Oper Ltd Pship	**54.4%**	57.6%	60.5%	6.0%	39.5%
Lincoln Natl Corp	**50.6%**	66.8%	66.8%	16.2%	33.2%
Cna Finl Corp	**50.3%**	62.0%	62.4%	12.1%	37.6%
John Deere Cap Corp	**50.6%**	54.8%	56.9%	6.4%	43.1%
Avalon Bay Cmntys Inc	**53.8%**	53.4%	57.7%	3.9%	42.3%
Loews Corp	**48.0%**	56.4%	57.2%	9.2%	42.8%
Liberty Mut Ins Co	**42.2%**	58.2%	58.1%	15.9%	41.9%
Goldman Sachs Gp Inc	**38.6%**	62.2%	63.1%	24.5%	36.9%
Genworth Finl Inc	**46.0%**	56.3%	56.7%	10.8%	43.3%
Hsbc Fin Corp	**49.6%**	67.4%	67.3%	17.8%	32.7%
JPMorgan Chase & Co	**41.3%**	62.9%	63.3%	22.0%	36.7%
Bk of America Corp	36.2%	61.2%	62.7%	26.5%	**37.3%**
Aon Corp	38.4%	49.2%	49.2%	10.8%	**50.8%**
Citigroup Inc	33.9%	61.8%	64.6%	30.7%	**35.4%**
Sears Roebuck Accep Corp	33.9%	31.1%	35.1%	1.2%	**65.0%**
Cap One Finl Corp	**40.0%**	63.2%	63.9%	23.9%	36.1%
Heller Finl Inc	**44.6%**	55.5%	55.8%	11.2%	44.2%
Morgan Stanley	33.3%	61.2%	64.2%	30.9%	**35.8%**
Gatx Corp	38.1%	36.4%	40.1%	2.0%	**59.9%**

Note: Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the sectorial risk. Column 6 displays the size of idiosyncratic risk, as 1.0 minus the adjusted R-squared in column 4.

Table 3.25: North American financial issuer CDS spread decomposition using GRF as the systemic explanatory variable (continued)

Issuer (1)	Systemic risk (2)	First PC (3)	Joint Regression (4)	Sectorial risk (5)	Idiosyncratic risk (6)
Wells Fargo & Co	**34.4%**	62.9%	65.9%	31.5%	34.1%
Marsh & Mclennan Cos Inc	28.5%	37.2%	37.1%	8.6%	**62.9%**
Merrill Lynch & Co Inc	30.4%	55.8%	58.5%	28.1%	**41.5%**
Health Care REIT Inc	41.5%	40.1%	43.9%	2.4%	**56.1%**
Intl Lease Fin Corp	**44.8%**	64.4%	64.4%	19.6%	35.6%
Philip Morris Cap Corp	33.1%	35.6%	37.0%	3.9%	**63.0%**
Mack Cali Rlty LP	47.6%	42.3%	48.9%	1.3%	**51.1%**
Natl Rural Utils Coop Fin Corp	36.7%	50.4%	50.3%	13.5%	**49.7%**
Amern Express Cr Corp	45.4%	35.2%	45.4%	0.0%	**54.6%**
Duke Rlty Ltd Partnership	34.1%	44.6%	44.5%	10.4%	**55.5%**
Istar Finl Inc	33.9%	41.9%	42.0%	8.1%	**58.0%**
MBIA Ins Corp	19.5%	36.7%	38.6%	19.1%	**61.4%**
MGIC Invt Corp	13.8%	32.4%	37.0%	23.2%	**63.0%**
MBIA Inc.	26.1%	43.1%	43.9%	17.8%	**56.1%**
Amern Intl Gp Inc	23.5%	40.9%	42.1%	18.6%	**57.9%**
Radian Gp Inc	30.6%	48.1%	48.6%	17.9%	**51.4%**
EOP Oper Ltd Pship	28.0%	28.2%	30.1%	2.1%	**69.9%**
Radian Asset Assurn Inc	23.9%	40.0%	40.8%	17.0%	**59.2%**
Healthcare Rlty Tr Inc	25.3%	22.9%	26.0%	0.7%	**74.0%**
SLM Corp	17.4%	29.3%	29.9%	12.5%	**70.1%**
Safeco Corp	24.4%	25.8%	26.9%	2.5%	**73.1%**
Odyssey Re Hldgs Corp	16.9%	21.6%	21.5%	4.6%	**78.5%**
Toyota Mtr Cr Corp	27.9%	18.7%	27.8%	-0.1%	**72.2%**
Fairfax Finl Hldgs Ltd	19.4%	19.6%	20.8%	1.5%	**79.2%**
Brookfield Asset Mgmt INC	19.3%	7.9%	22.2%	2.9%	**77.8%**
Charles Schwab Corp	15.2%	9.7%	15.2%	0.0%	**84.8%**
Amern Finl Gp Inc	17.4%	13.8%	17.3%	0.0%	**82.7%**
Highwoods Rlty LP	7.1%	5.9%	7.0%	0.0%	**93.0%**
Legg Mason Inc	0.0%	0.2%	0.0%	0.0%	**100.0%**
Franklin Res Inc	2.2%	0.4%	3.0%	0.8%	**97.0%**

Note: Column 2 displays the adjusted R-squared from a regression on the global risk factor (GRF) as the explanatory variable. Column 3 shows the adjusted R-squared from a regression on the first principal component for the North American financial issuers contained in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the sectorial risk. Column 6 displays the size of idiosyncratic risk, as 1.0 minus the adjusted R-squared in column 4.

Chapter 4

Basis risk in hedging a CDS portfolio with credit indices

4.1 Introduction

The Basel Committee (2011) issued the document “Basel III: A global regulatory framework for more resilient banks and banking systems” in which it establishes the methodology for the computation of the capital charge for CVA risk. CVA is the adjustment by credit valuation of the derivative portfolio. The determination of the credit spread is crucial for the quantification of the CVA. The document is very prescriptive, with each entity using the CDS issuer spread if possible, and if not, then, using a proxy spread based on the rating, industry and region of each counterparty. In a later document, “Basel III counterparty credit risk and exposures to central counterparties - Frequently asked questions”, the Basel Committee (2012b) reaffirms this idea, requiring financial entities to estimate the credit spread curves taking into account the same factors of rating, sector and region of each counterparty.

On the other hand, a recent article, “CDS de-correlation a threat to CVA hedging, traders warn” on 3 September 2014 [see Devasaba (2014)], directly sourced from Risk, highlights the climate of fear prevalent throughout the industry.

“The ongoing slump in traded volumes of single-name credit default swaps (CDSs) is a "nasty side effect" of international regulatory reforms, a senior banker has claimed, raising fears that credit valuation adjustment (CVA) hedging will become increasingly difficult should the long-standing correlation between single-name and index CDS products break down. “

“As single-name volumes wither, notional outstanding in index CDS products is growing, raising fears that the long-standing correlation between CDS indexes and single-name contracts is in danger of breaking down – a consequence of tougher margin regimes and trading restrictions that have forced many credit arbitrage players

out of the market."

"There is more basis noise in the indexes. The credit indexes can deviate – sometimes quite significantly – from the CDS spreads of the constituent names at the first sign of volatility," says a credit trader at a hedge fund in New York."

"The main CDS indexes are fairly liquid and generally trade several hundred times a day, but many single names can go for long periods without a single transaction. That means the indexes react quickly to any changes in risk whereas single names often lag the indexes and can see quite dramatic price moves."

There are other recent articles on Risk.net which deal with these implications in the CDS market as: "Corporates fear CVA charge will make hedging too expensive" by Watt (2011) or "Proxy war: Shrinking CDS market leaves CVA and DVA on shaky ground" by Carver (2013b) among others [see Carver (2013a) and Deventer (2012)]. Finally, in another more recent Blomberg article on 9 September 2014, Cairn Capital Ltd. supported the strategy on the options of European credit derivatives indices to hedge the risk that Scotland would vote for independence from the U.K. "Given the uncertainty over the outcome, potential impact on markets and the technicals in markets where short positions can be very painful, I prefer macro hedges through options to anything single-name specific," said Andrew Jackson, chief investment officer at Cairn Capital in London.

Therefore, in this chapter, we would like to have an estimation of the basis risk between the CDS portfolio and the hedge with different indices [see Gregory (2012)], and we will answer, among others, the following questions: Is the basis risk higher in North America than in Europe? Does the effectiveness of the hedge increase when we consider more than one to hedge the portfolio? Could we improve the results using a different estimation technique from OLS? Could we really hedge the Jump-to-Default risk?

This chapter is divided into seven sections: In Section 4.2 we introduce the different indices that we have used. In Section 4.3 we detail the dataset that we have used. In Section 4.4 we present the framework for the hedge, and the different employed hypothesis. In Section 4.5 we focus on the results of these methodologies. In Section 4.6 we look up the concept of Jump-to-Default risk. And finally we present the main conclusions in Section 4.7.

4.2 CDS index products

A credit index can usually be thought of as an equally weighted combination of single-name CDS and hence the fair premium on the index will be close to the average (weighted by each issuer dollar value of a one basis point change, DV01) CDS premium within that index. A credit index is normally used to hedge credit risk or to take a position on a basket of credit entities (a CDS index is a portfolio of actively traded liquid names in a particular sector of the market). A credit default swap index is standardized, therefore highly liquid and trades on a very small bid-offer spread. This makes it is a primary market vehicle for gaining diversified credit exposure. Credit indices are easy and efficient to trade: investors can express their bullish or bearish sentiments on credit as an asset class, and portfolio managers can manage their credit exposures actively.

The two most common and liquid credit indices are the iTraxx Europe and CDX North American Investment Grade, CDX NA IG (the difference between them is shown in Figure 4.1). The benchmark Markit iTraxx Europe Index comprises 125 equally-weighted European names. A HiVol Index consisting of the 30 widest spread non-financial names and three sector indices are also published. The Markit iTraxx Crossover Index comprises the 45 most liquid sub-investment grade entities. The Markit iTraxx Europe indices trade 3, 5, 7 and 10-year maturities and a new series is determined by a dealer liquidity poll every six months. The Markit CDX indices are a family of indices covering multiple sectors in North America. The main indices are: Markit CDX North American Investment Grade (125 names), Markit CDX North American Investment Grade High Volatility (30 names from CDX IG), Markit CDX North American High Yield (100 names). Buying CDS protection on \$125m of the CDX NA IG Index is almost equivalent to buying \$1m of CDS protection on each of the underlying reference entities within the index. The Markit CDX indices roll semi-annually in March and September. The other indices exist for different underlying reference entities and regions but they are less liquid.

Furthermore, the spread (in basis points) represents the annual compensation the protection seller receives for agreeing to pay any losses due to the default of any of the firms in the index in the following 5-years. Assuming a 100 basis points spread, for instance, for iTraxx Europe and a contract notional of 100 million euros, the protection seller will receive 1,000,000 euros per year as long as there is no default in the index companies. Since iTraxx is an equally weighted portfolio, the exposure to each company is 0.8% (=1/125) of the contracted notional, i.e. 800,000 euros. If a company in iTraxx were to default with a 50% loss, the protection seller would pay 400,000 euros to the protection buyer at the time of the default assuming cash settlement. From then on, the new index would only have 124 companies, the contracted notional would be reduced by 800,000 euros to 99.2 million and the protection seller would keep receiving 100 basis points per year on the new notional.

Credit indices have expanded dramatically in recent years, with volumes rising, trading costs decreasing, and a growing visibility across financial markets. We show a summary for the different existing credit indices in Figure 4.2. The benefits of using CDS indices include the following:

Tradability: Credit indices can be traded and priced more easily than a basket of cash bond indices or single-name CDS

Liquidity: Significant liquidity is available in indices and has also driven more liquidity in the single-name market

Operational Efficiency: Standardized terms, legal documentation, electronic straight-through processing

Transaction Costs: Cost efficient means to trade portions of the market

Industry Support: Credit indices are supported by all major dealer banks, buy-side investment firms, and third parties (for example, Markit offers transaction processing and valuations services)

Transparency: Rules, constituents, fixed coupon, and daily prices are all available publicly

Figure 4.1: Differences between iTraxx and CDX

	iTraxx	CDX
Region	Europe, Asia and Emerging Markets	North America and Emerging Markets
Credit Event	Bankruptcy, Failure to Pay, Modified Restructuring	Bankruptcy, Failure to Pay
Currency	Europe – EUR Japan – JPY Asia ex-Japan – USD Australia – USD	USD, EUR
Reference Entities	A liquidity poll decides inclusions and exclusions	A rules-based approach, that takes into account liquidity (as well as sectors and ratings for high yield names), determines inclusions and exclusions
Business Days	London and TARGET Settlement Day	USD – New York and London EUR – London and TARGET Settlement Day

Source: Markit (2009c)

An important feature of credit indices is that they "roll" every six months, involving:

1. Adjustment of maturity. Typical traded maturities are 5, 7 and 10 years. Fixed maturity dates will be used such that the initial maturities are 5.25, 7.25 and 10.25 years. After six months, the maturities will have become 4.75, 6.75 and 9.75 and these will be re-set to their original values.

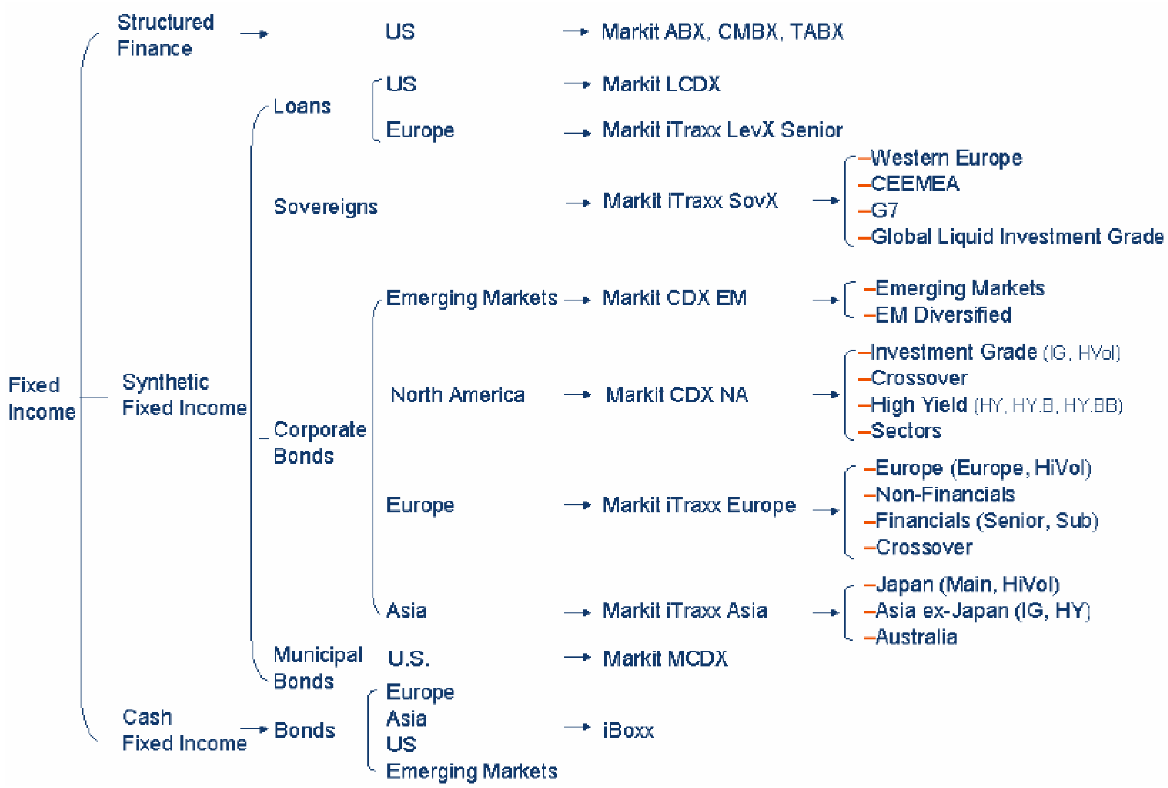
2. Adjustment of portfolio. Names will be removed from a credit index according to predefined criteria in relation to credit events, ratings downgrades and increases in individual CDS premiums beyond a certain threshold. The overall aim is to replace defaulted names and maintain a homogeneous credit quality. Names removed from the index will be replaced with other names meeting the required criteria.

3. Premium. In the 6-month period before a roll, the index premium is fixed at a given level of either 100 or 500 bps and trades on the index will involve an upfront payment from one party to the other to compensate for the difference between the fair premium and traded premium.

4.3 Input data

In this study, we use the daily senior 5-year CDS contract with the standard currency and restructuring clause for each issuer of the sample. We use this particular criteria because of its liquidity and representativeness. The analysed period is from 2006 to 2012 because we think that it is the most relevant period of time for the credit market.

Figure 4.2: Markit credit and loan indices overview



Source: Markit (2009c)

Table 4.1: Issuer distribution by industry region

Industry/Region	Europe	Japan	N.Amer	Total
Basic materials	17	13	33	63
Consumer goods	33	23	54	110
Consumer services	35	16	52	103
Energy	6	3	33	42
Financials	69	17	61	147
Health care	4		24	28
Industrials	30	24	46	100
Technology	5	8	16	29
Telecommunication services	20	3	14	37
Utilities	27	9	27	63
Total	246	116	360	722

Our sector classification is based on the ICB criteria, (Industry Classification Benchmark), which distinguishes four levels: Industry, supra-sector, sector and subsector. In this case, Markit works with the industry level, differentiating eleven industries: financials, health care, energy, telecommunication services, basic materials, utilities, industrials, technology, consumer goods, and consumer services.

The criteria to be in the sample are summarized here: In this case we have just considered those issuers that have priced every day in the senior 5-year CDS contract. According to these criteria, we have used a sample of 722 issuers. The different geographies contained in the Markit database are: Africa, Asia, Caribbean, Eastern Europe, Europe, India, Latin America, Middle East, North America, Oceania, Offshore, Pacific and Supra. However, most of these 722 issuers are located in Europe, North America and Asia. Table 4.1 summarises the issuer distribution by industry and region.

Finally, we use the iTraxx Europe Index, the HiVol iTraxx Europe Index, the iTraxx Europe Crossover Index, the CDX NA IG Index, the CDX Index, the CDX North American High Yield Index and the iTraxx Japan Main Index as hedges in the different analysed exercises.

4.4 A framework for the hedge

In this section we explain all the details that we have used in order to calculate the mark-to-market of the CDS portfolio for the different analysed regions: Europe, North America, and Japan. [1] We suppose that we have one monetary unit in each issuer of the sample during all the analysed periods of time. We are therefore long in the credit market as it is natural for a financial institution. In this case, our loss in the portfolio will be the result of an increase in the CDS of each issuer. Thus, the natural hedge of this portfolio will be to take the opposite contract in their credit index (depending on the issuer's region). Then we carry out the following steps for the analysis:

1. Firstly, we average weekly the spread of each issuer in order to avoid the excessive daily market noise of

[1] We use the 'plyr', Wickham (2014), and 'TTR',Ulrich (2014), R packages for these exercises

the analysed period. Therefore, we have now 365 weekly CDS for each issuer.[2]

2. We do the same, with the six credit indices that we use for the the hedge in the different exercises: the iTraxx Europe, iTraxx Europe Crossover and HiVol iTraxx Indices to hedge the European issuers, the CDX NA IG and High Yield CDX Indices to hedge the North American issuers, and the Japan Main Index for Japanese issuers.

3. We approximate the difference of the mark-to-market of each CDS weekly of the firm i in time t as (being long in the CDS)[3]:

$$\Delta MtM_t^i = -(CDS_t^i - CDS_{t-1}^i)RD_{t-1}^i \tag{4.1}$$

RD_t^i is the risky duration of the issuer i at the time t, and is computed as:

$$RD_t^i = \sum_{t=1}^{n} S_t \tau_{t-1,t} FD_t \tag{4.2}$$

where S_t is the survival probability at the time t, τ is the time in years between two consecutive payment dates, FD_t is the discount factor at time t, and n is the total number of payments in a CDS contract. On the other hand, we can express the discount factor over the time interval $[x, x+t]$ as $FD_t = e^{-\int_0^t r(s)ds} = e^{-rt}$, where r is the instantaneous spot risk-free rate, assuming a constant spot rate over that time interval. In addition, as we have shown in equation (2.12) the survival probability over the time interval $[x, x+t]$ can be expressed as $S_t = e^{-\int_0^t h(s)ds} = e^{-ht}$, where h is the hazard rate, assumed to be constant. [4] We get

$$RD_t^i = \int_0^T exp\left[\left(-CDS_t^i/(1-R_t^i) + r_t\right)\right] dt = \frac{1 - exp\left[\left(-CDS_t^i/(1-R_t^i) + r_t\right) T\right]}{CDS_t^i/(1-R_t^i) + r_t} \tag{4.3}$$

Thus, if we assume that the payment of the premium leg takes place in continuous time, we can approximate the risky duration as in the equation (4.3), where R_t^i is the recovery of the issuer i in time t, r is the instantaneous spot risk-free rate interest rate at time t of the currency of the CDS contract, and T is the tenor of the contract, in our case five years.

4. We do the same calculus than in 3 for the credit indices obtaining the difference of the mark-to-market of each credit index j,

$$\Delta MTM_t^{Index_j} = -(Spread_t^{Index_j} - Spread_{t-1}^{Index_j})RD_{t-1}^{Index_j} \tag{4.4}$$

[2] As explained later, we also use daily data for comparison.

[3] We are also assuming in order to simplify that we can roll over the CDS contracts of the issuers and the credit indices every week.

[4] Therefore, by applying the standard market CDS recovery for each issuer, we can extract the hazard rate from CDS prices; the hazard rate, h, is approximated by $h = \frac{CDS_i^{5y}}{(1-R_i)}$. This approximation is standard among practitioners and is known as the credit triangle that relates the spreads, default probabilities, and recovery rates as we detail in Section 5.3 in the next chapter, [see for more details White (2013)].

5. We calculate a weekly beta for each issuer i with respect to their credit index j as

$$Beta_t^i = Cov(\Delta MtM_t^i, \Delta MTM_t^{index_j}) / Var(\Delta MTM_t^{index_j}) \tag{4.5}$$

   We use a time window of 52 observations, a year to estimate $Beta^i$ using a rolling window. Therefore, we have finally 313 weekly observations.

6. We get the difference of the mark-to-market in t time of each unheeded regional j portfolio as

$$\Delta MtM(UH)_t{}^{Region_j} = \sum_{i=1}^{n_j} \Delta MTM_t^i / n_j \tag{4.6}$$

   where n_j is the total number of the issuers in that region in the analysed sample.

7. We get the difference of the mark-to-market in t time of the hedged regional j portfolio as

$$\Delta MtM(H)_t{}^{Region_j} = \sum_{i=1}^{n} \Delta MTM_t^i / n - \sum_{i=1}^{n} Beta_{t-1}^i \Delta MTM_t^{index_j} / n \tag{4.7}$$

   where n is the total number of the issuers in that region in the analysed sample.

8. For the global portfolio we aggregate[5] the results of each one of the three regions, Europe, North America and Japan in time t. Then we get:

$$\Delta GlobalMtM(UH)_t = \sum_{j=1}^{3} \Delta MtM(UH)_t{}^{Region_j} \tag{4.8}$$

   and

$$\Delta GlobalMtM(H)_t = \sum_{j=1}^{3} \Delta MtM(H)_t^{Region_j} \tag{4.9}$$

9. Finally, we can calculate the accumulated of the mark-to-market of the portfolio in time T as:

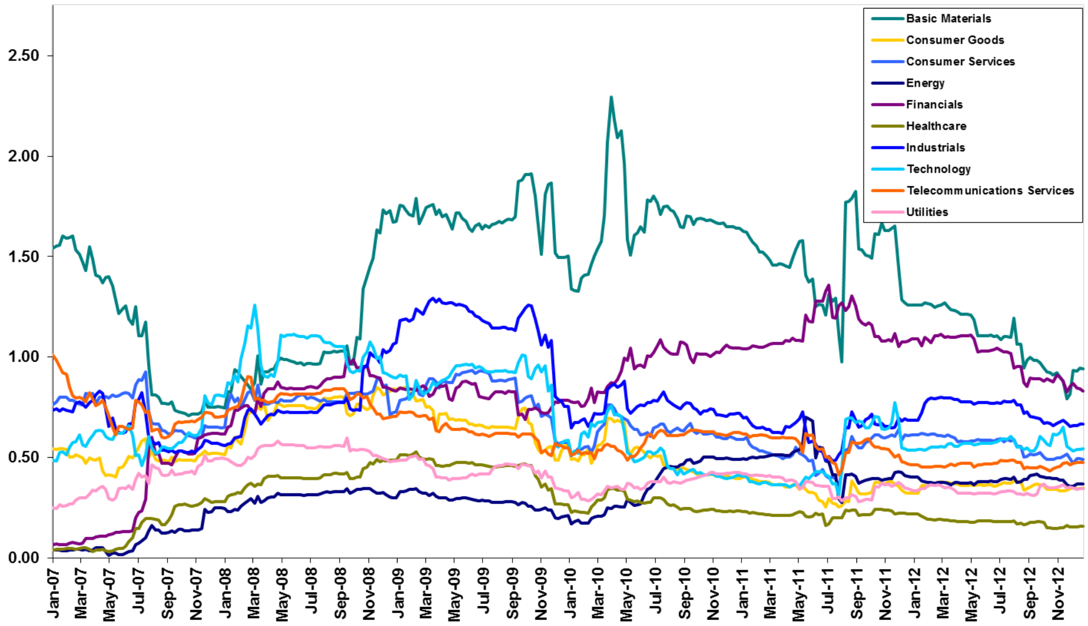
$$Ac\Delta GlobalMtM(UH)_T = \sum_{t=1}^{T} \Delta GlobalMtM(UH)_t \tag{4.10}$$

   and

$$Ac\Delta GlobalMtM(H)_T = \sum_{t=1}^{T} \Delta GlobalMtM(H)_t \tag{4.11}$$

[5] It is implicit that we are assuming a constant exchange rate equal to 1 between the Euro, USD, and the Yen.

Figure 4.3: Sectorial median beta estimates for the European CDS portfolio. 2007-2012



4.5 Results

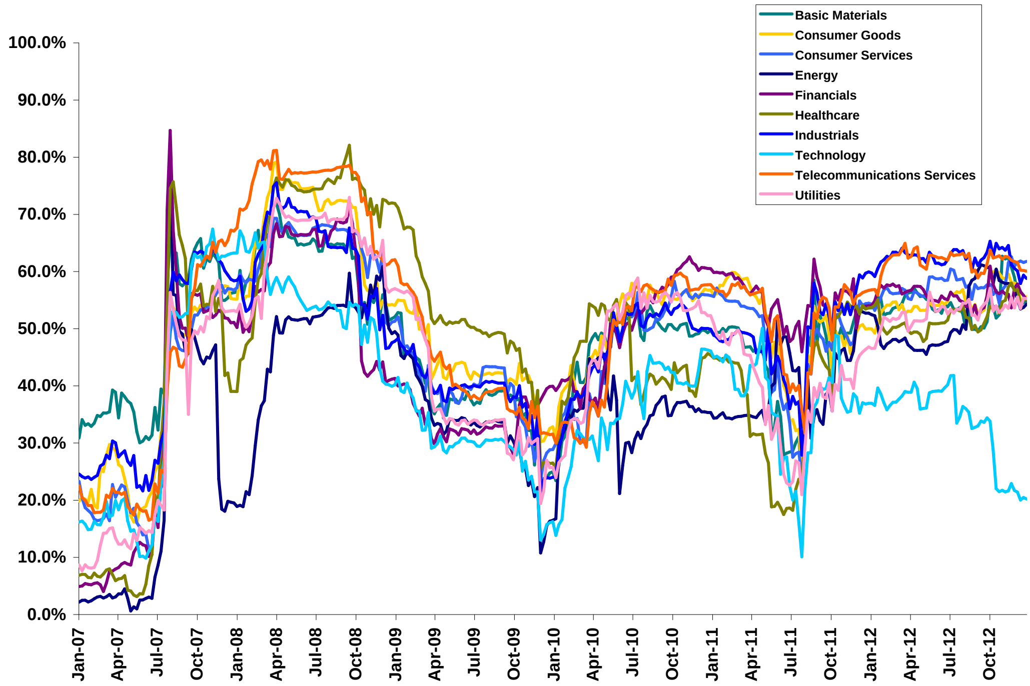
4.5.1 Beta analysis

In this first section, we explore the beta coefficients of the different sectors. These estimated beta coefficients represent a measure of the systemic risk of each sector. This means that when the beta is higher than 1, we need to hedge each unit of the notional of that sector, with a greater than 1 unit of the credit index notional. A beta greater than 1 can be explained mainly by the volatility CDS in that sector is higher than the observed volatility spread in the credit index.

The results for the median beta sector estimates for the European Portfolio are represented in Figure 4.3. We can see that the sectors with the lowest median beta during the crisis were energy and health care and the one with the highest was the basic material sector. The evolution of the financial beta estimate is also significant, being very small before the crisis and then even greater than 1 during 2010, reflecting that this global crisis was overall a financial global crisis. These results are also interesting for asset allocation proposals, as they give a clear sign of the systemic risk of the different industries.

Moreover, the financial industry has a growing fear as single-name volumes wither, and notional outstanding in index CDS products grows, that the correlation between CDS indices and single-name contracts is in danger of breaking down. We show the median sector R-squared in Figure 4.4, using Europe iTraxx as a credit index, for the European portfolio during 2007-2012. It is clear that at least during the analysed period (2007-2012) the R-squared between the different European sectors and the credit index was even higher, during the

Figure 4.4: Sectorial median R-squared for the European CDS portfolio. 2007-2012



worst period of the crisis (2008-2009), reflecting what we normally observe normally during crises, a generalised increase in the correlation level. Therefore the market sentiment of the financial industry [see Devasaba (2014)] cannot be justified with this dataset, but it would be interesting to follow the evolution of this type of graph in coming years.

Finally, we show the results for the North American portfolio. In this case, the sector with the highest beta is usually the financial sector, and the smallest one is the health care sector as in the European case (Figure 4.5). In terms of the R-squared (Figure 4.6) the trend is the same as in Europe in general, but the level of R-squared is lower, which implies that the CDX Index is not as good as iTraxx for hedging this portfolio. This point will be analysed in-depth in the next section.

4.5.2 Hedge results

4.5.2.1 European CDS portfolio analysis

In this subsection, we firstly show the weekly profit and loss (P&L) for the European CDS portfolio and the P&L, considering the weekly hedge for the period 2007-2012. Figure 4.7 is a scatterplot of the returns of the unhedged portfolio versus the returns of the hedge portfolio. We clearly observe the huge deterioration of the credit market during the crisis, the losses for some weeks being higher than 100 basis points for the whole European portfolio. If we direct our attention to the hedge portfolio, it is clear that the Markit iTraxx Europe Index normally works quite well, reducing the market movements. However, there is a basis risk that cannot be ignored, and this basis risk obviously increases with the volatility of the market. It is also interesting to observe

Figure 4.5: Sectorial median beta estimates for the North American CDS portfolio. 2007-2012

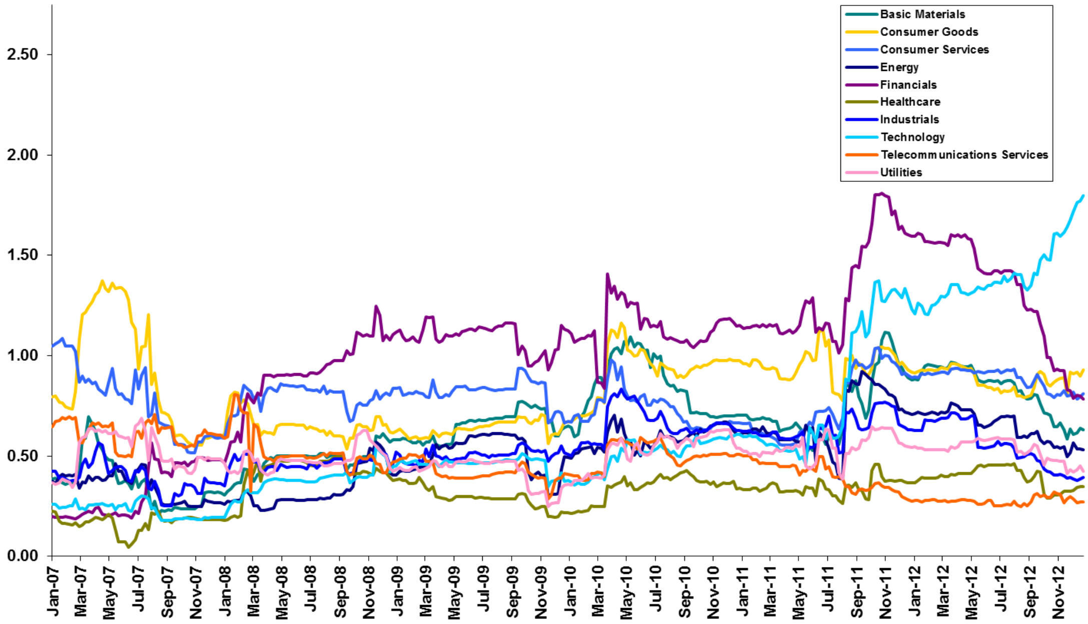


Figure 4.6: Sectorial median R-squared sector for the North American CDS portfolio. 2007-2012

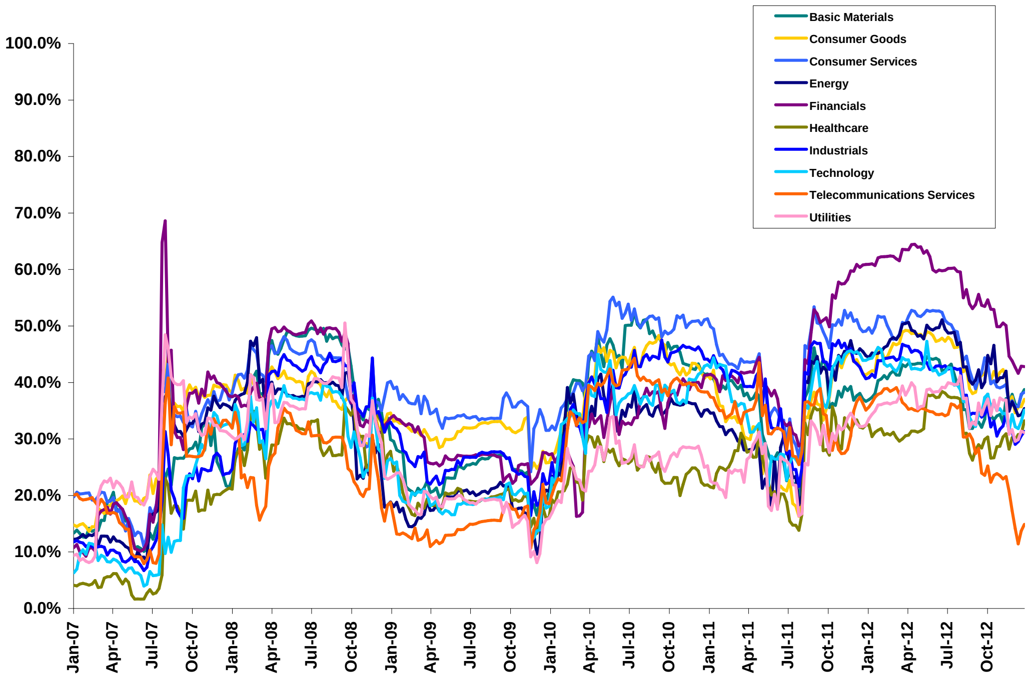
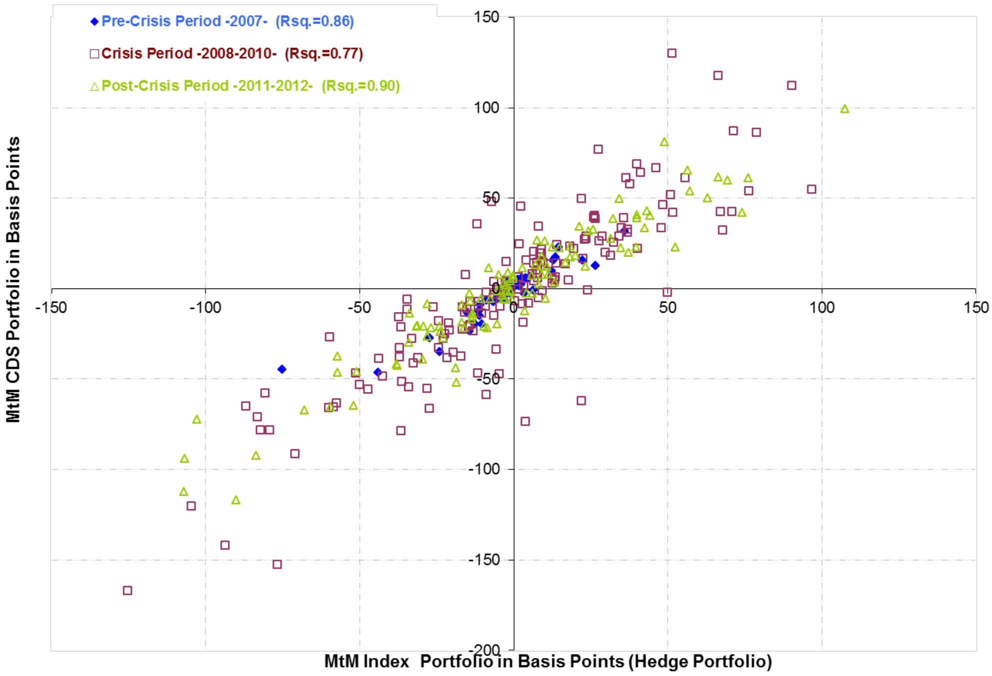


Figure 4.7: Weekly profits and losses for the European CDS and hedge portfolios. (246 issuers) in basis points. 2007-2012



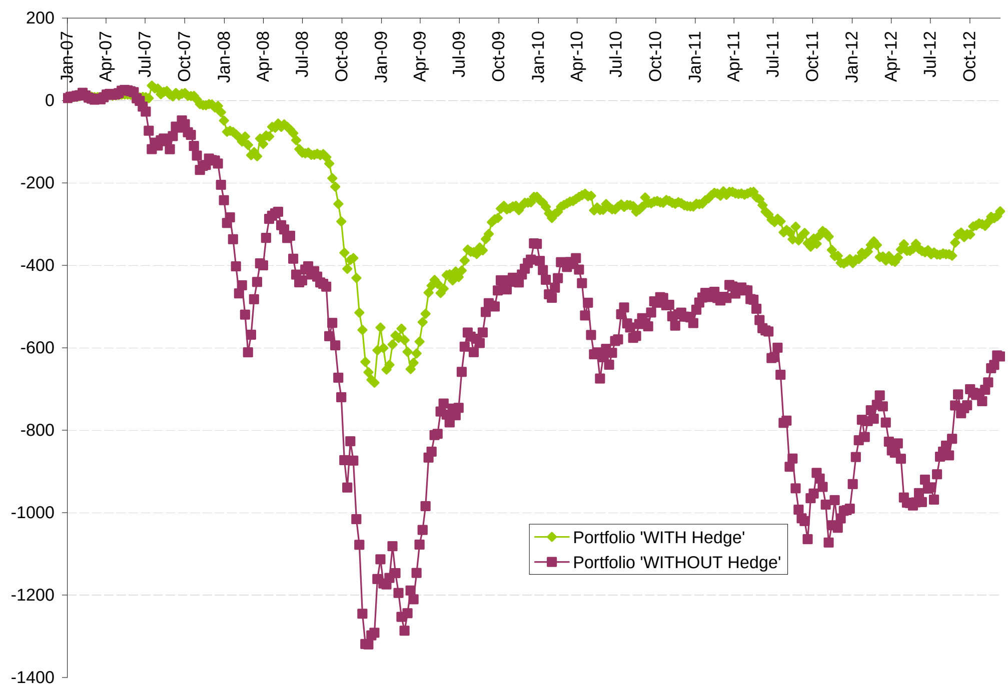
Note: Rsq. = R-squared

that the hedge portfolio worked better during the pre- and post-crisis periods, with an R-squared higher than 85% for each of the two periods in contrast to an R-squared of 77% during the crisis period. Without any doubt, the main problems of this hedge are shown by the points that are a loss for the CDS portfolio and a profit for the index hedge portfolio, representing a "double" loss, as we have the opposite contract in the hedge portfolio. In those points, we have a negative correlation between the CDS portfolio and its hedge.

In Figure 4.8 we have just added the weekly P&L in order to get the accumulated P&L during the period 2006-2012 for the European credit portfolio, ignoring the discount factor to aggregate the P&L. Again, the devastating effect of the recent crisis in terms of market losses is clear. It is also noteworthy that after some weeks of very high losses, we normally observe an opposite market reaction. This fact could be explained by some active measures from regulators and governments, as we detail in the next chapter. In addition, this graph reflects the general increase in the credit spread market in the period 2006-2012. In terms of the hedged portfolio, we observe that we can reduce losses hedging with iTraxx, but in no case we can totally immunize the value of the portfolio.

Finally, we show the weekly VaR (right axis), and the empirical density function of the weekly P&L for the European portfolio (left axis), Figure 4.9. If we look at either the red line or the blue, we get the historic probability of having a loss higher than the value in the X axis. For example, the probability of having a weekly loss higher than 70 basis points is 4.81% for the non-hedged portfolio and just 0.96% for the hedged portfolio. These results are very interesting in order to establish a VaR limit or a stop loss on the basis risk. On the other hand, if we observe the density function projected over the right axis, it is very clear that most of the time, almost 65%,

Figure 4.8: Accumulated profits and losses in basis points for the European CDS portfolio.(246 issuers). 2007-2012



the effectiveness of the hedge is quite good, the mark-to-market of the hedged portfolio being very close to zero (represented by the probability that the mark-to-market of the hedged portfolio is between zero and ten basis points).

4.5.2.2 North American CDS portfolio analysis

In the North American case, consisting of a portfolio of 360 issuers, the results of the hedge show a pattern similar to the European portfolio. Figure 4.10 is a scatterplot of the returns of the unhedged portfolio versus the returns of the hedge portfolio. It is important to mention that even though the North American portfolio is more diversified than the European portfolio in terms of the numbers of issuers, the results of the hedge are worse. On the other hand, we see the same pattern as before in terms of the R-squared, meaning that the effectiveness of the hedge is higher during the non-crisis periods than during the crisis period, as reflected by the R-squared of the graph. In Figure 4.11, it can be observed that this was a global crisis, as the most devastating consequences occurred after the Lehman Brothers default, with the widest increasing level of spread in North America, in the epicentre of the problem at that moment.

Finally, the empirical probability of having a weekly loss higher than 70 basis points is 8.97% for the non-hedged portfolio (Figure 4.12), in contrast to the 4.81% of the European case. This probability is 3.21% for the North American hedged portfolio, and just 0.96% for the European hedged portfolio. In terms of the ef-

Figure 4.9: Empirical density function for the weekly P&L and the weekly VaR for the European CDS portfolio. (246 issuers). 2007-2012

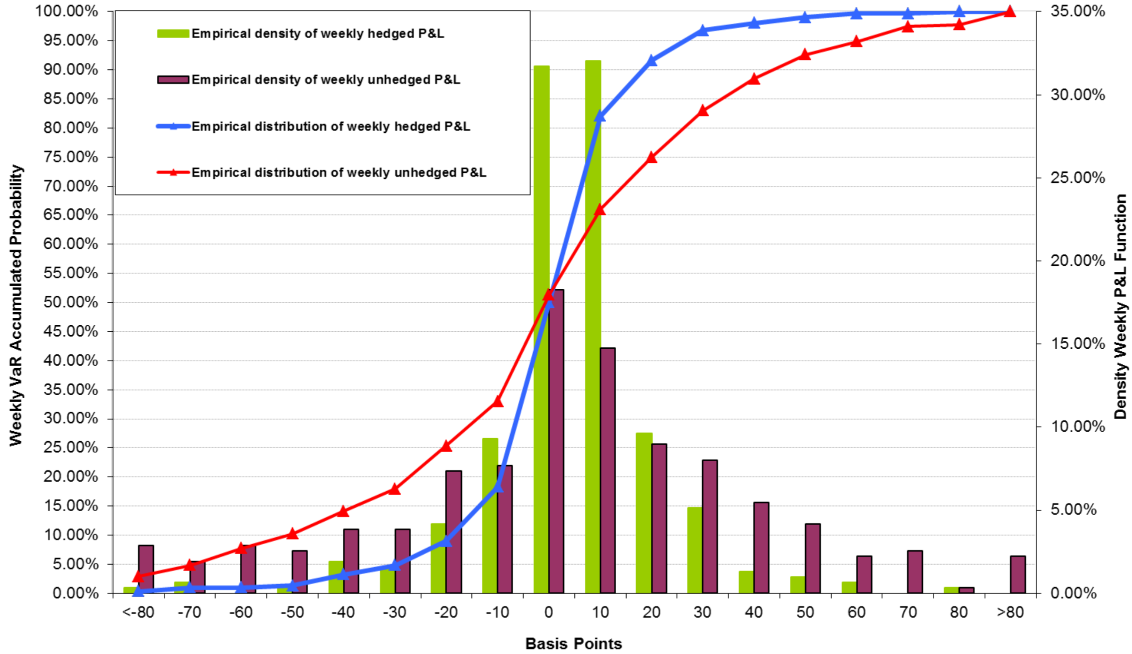
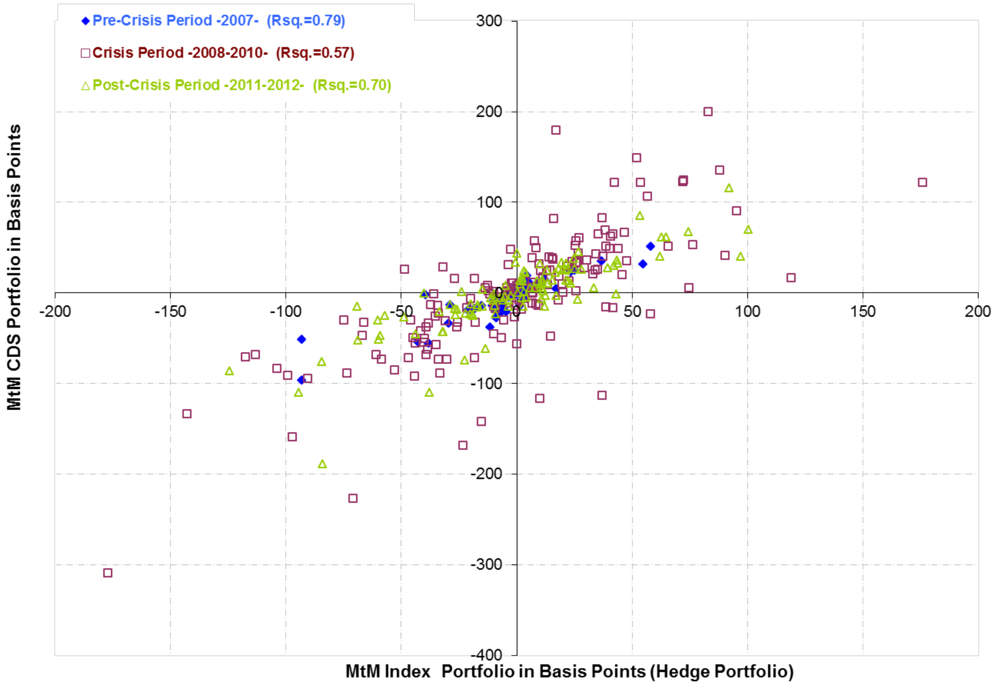
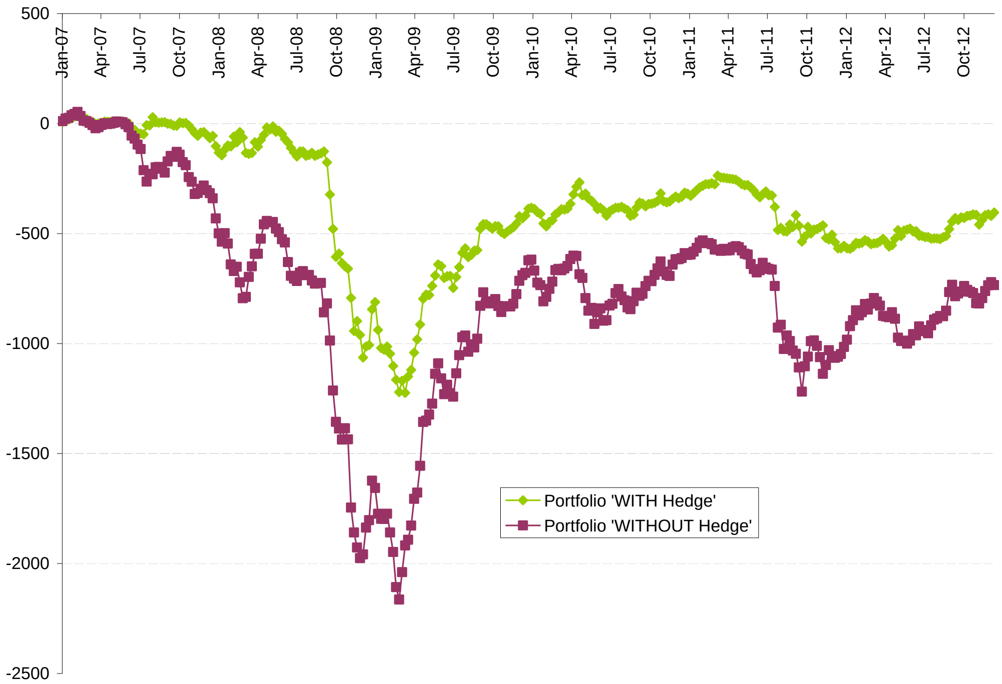


Figure 4.10: Weekly profits and losses for the North American CDS and hedge portfolios in basis points. (360 issuers). 2007-2012



Note: Rsq. = R-squared

Figure 4.11: Accumulated profits and losses in basis points for the North American CDS portfolio. (360 issuers). 2007-2012

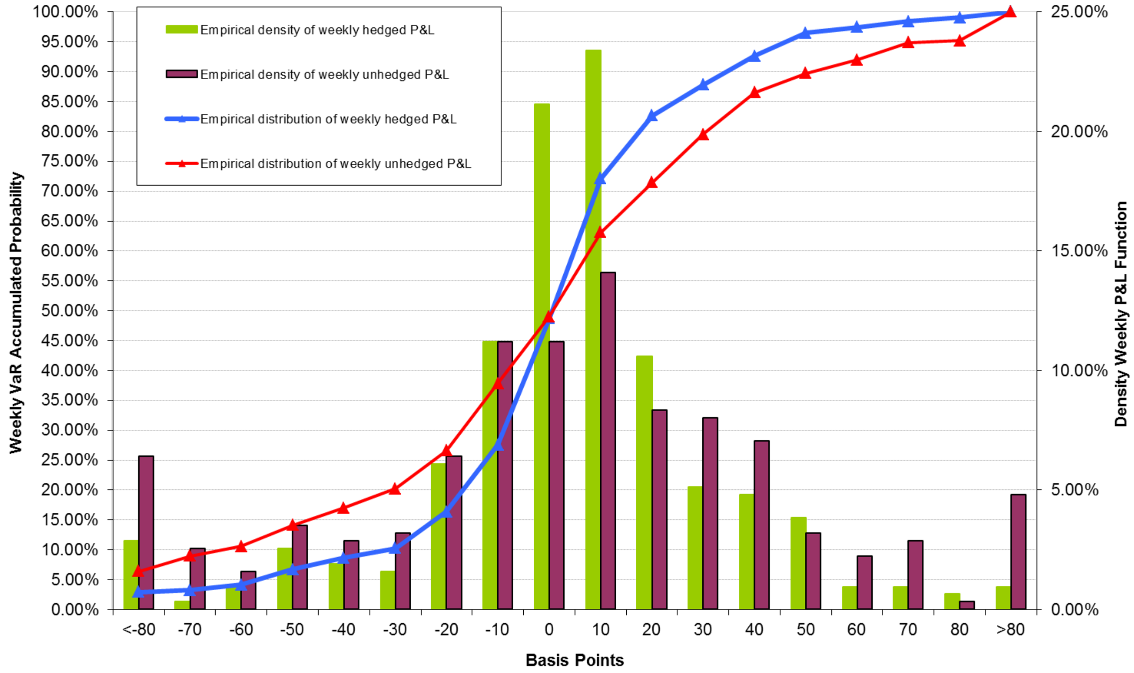


fectiveness of the hedge (right axis) and represented by the probability that the mark-to-market of the hedged portfolio is between zero and ten basis points, this number is 44.45%. Again, it is lower than in the European case, but it represents a ratio of almost 2 in relative terms of the effectiveness of the non-hedged portfolio (25%), quite similar to the European case.

4.5.2.3 Japanese CDS portfolio analysis

In the Japanese case, Figure 4.13 is a scatterplot of the returns of the unhedged portfolio versus the returns of the hedge portfolio. It consists of a portfolio of 116 issuers, and the results are similar to the previous cases, reflecting the importance of this global credit crisis. In terms of the weekly losses, we can observe that the non-hedged portfolio normally has a loss smaller than 100 basis points, which is lower than in the previous cases. This can be explained by the fact that the level of Japanese spreads is lower than in the rest of the world. In terms of the effectiveness of the hedge, we see that the R-squared is very close to 60% during the three analysed periods of time, in contrast to the European and North American cases. Figure 4.14 reflects the same as in the rest of the world, the general increase of the credit spread taking place in 2006-2012. In terms of the hedged portfolio, we observe that we can reduce the losses by hedging with Japan iTraxx, but in no case can we immunize completely the value of the portfolio. Finally, the empirical probability of having a weekly loss higher than 70 basis points is 5.00% for the non-hedged portfolio (Figure 4.15), in contrast to the 4.81% of the European case. This probability is 1.28% for the Japanese hedged portfolio, and similar to 0.96% for the

Figure 4.12: Empirical density function for the weekly P&L and the weekly VaR for the North American CDS portfolio. (360 Issuers). 2007-2012



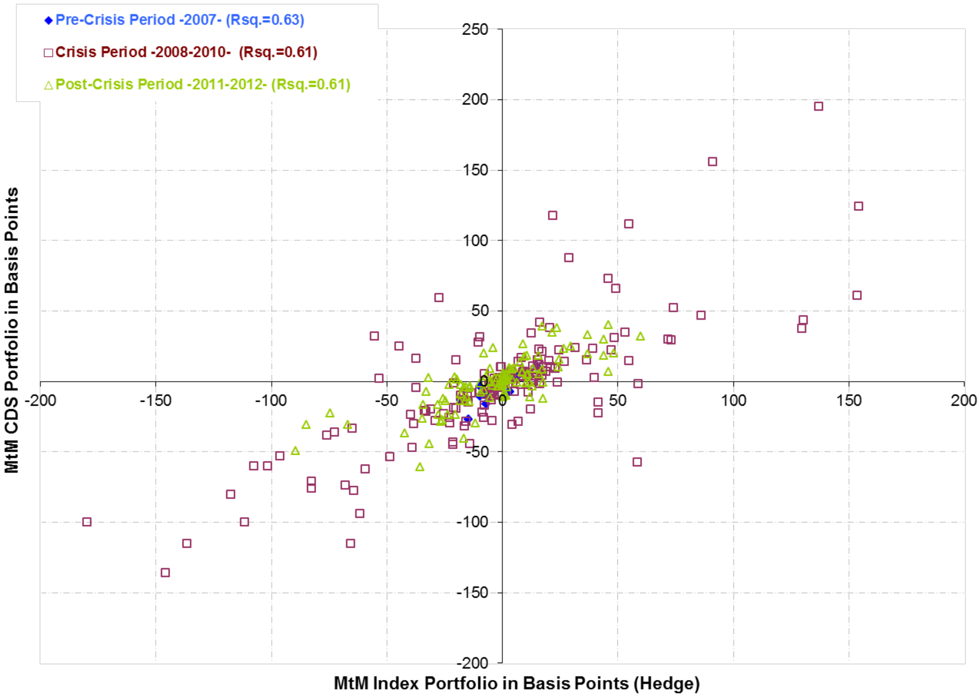
European hedged portfolio, showing that the hedge worked quite well.

4.5.2.4 Global CDS portfolio analysis

In this last exercise, we show the results of the aggregated global portfolio (European, North American and Japanese cases), considering an equal exposure in each issuer, and ignoring the effect of the foreign exchange rates, as we would like to focus on just the credit market and the hedge of the credit market. The most relevant fact is that in this case we are considering a portfolio of 722 issuers. Therefore, it may be thought that the results of the hedge will be better than in the previous case, as in the law of large numbers. However, in general terms, the results are a little worse than in the European case, due to the influence of the North American issuers[6] in the global portfolio and the high correlation among the weekly worst individual issuer hedges at the end of 2008 (Lehman default). Consequently, the benefits from the diversification decreased, and the basis risk could not be fully eliminated, as shown in Figures 4.16 and 4.17. Once again, we observe that the R-squared in terms of the effectiveness of the hedge is higher during the non-crisis period than during the crisis period. Finally, the probability of having a weekly loss higher than 70 basis points was 7.04% for the non-global hedged portfolio (Figure 4.18). This probability is 2.24% for the global hedged portfolio, higher than 0.96% for the European hedge portfolio. Again, the results are influenced by the performance of the North American portfolio, where the increase of the level of the credit spread was higher.

[6] In the previous chapter, we have also shown that the decomposition risk of the North American industrial and financial sectors are more influenced by the specific firm risk than in the European case.

Figure 4.13: Weekly profits and losses for the Japanese CDS and hedge portfolios. (116 issuers) in basis points. 2007-2012



Note: Rsq. = R-squared

Figure 4.14: Accumulated profits and losses in basis points for the Japanese CDS portfolio. (116 Issuers). 2007-2012

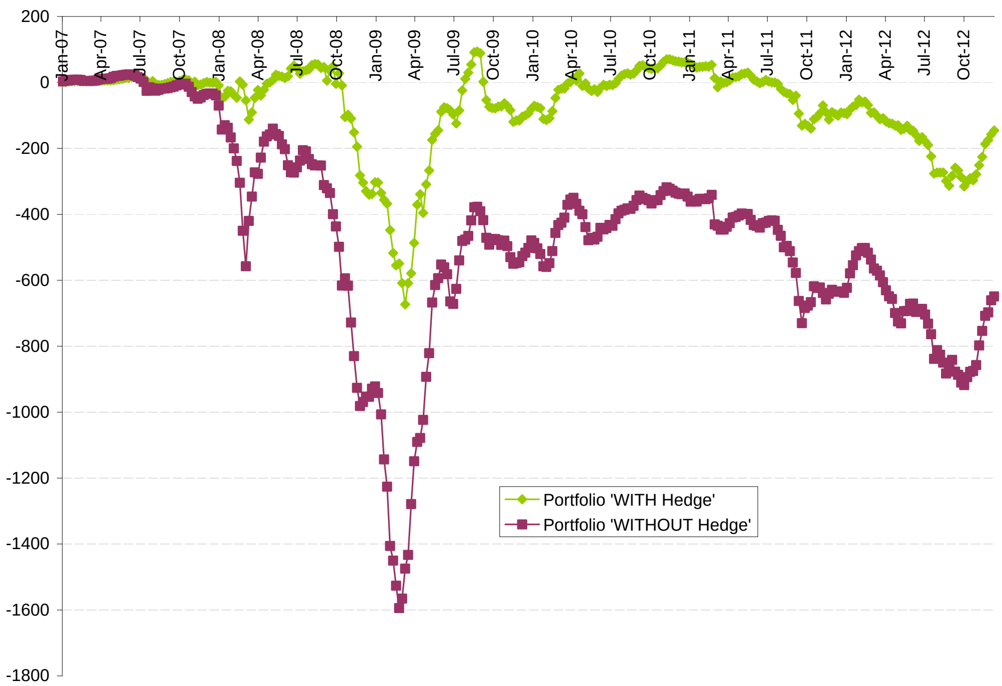


Figure 4.15: Empirical density function for the weekly P&L and the weekly VaR for the Japanese CDS portfolio. (116 issuers). 2007-2012

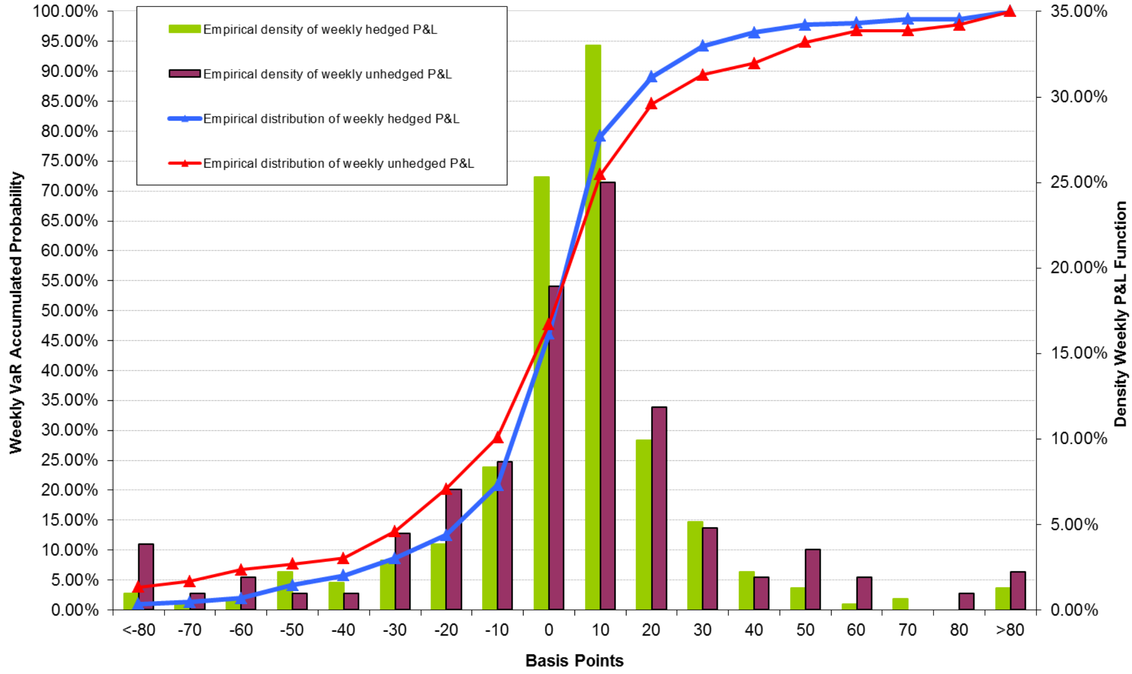
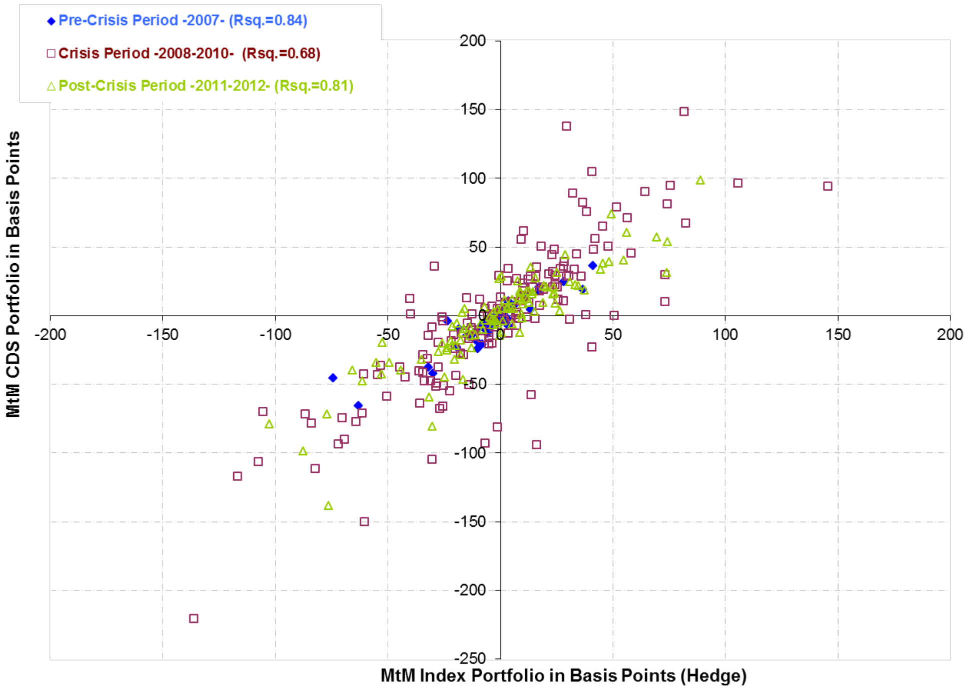


Figure 4.16: Weekly profits and losses for the global CDS and hedge portfolios. (722 issuers) in basis points. 2007-2012



Note: Rsq. = R-squared

Figure 4.17: Accumulated profits and losses in basis points for the global CDS portfolio. (722 issuers). 2007-2012

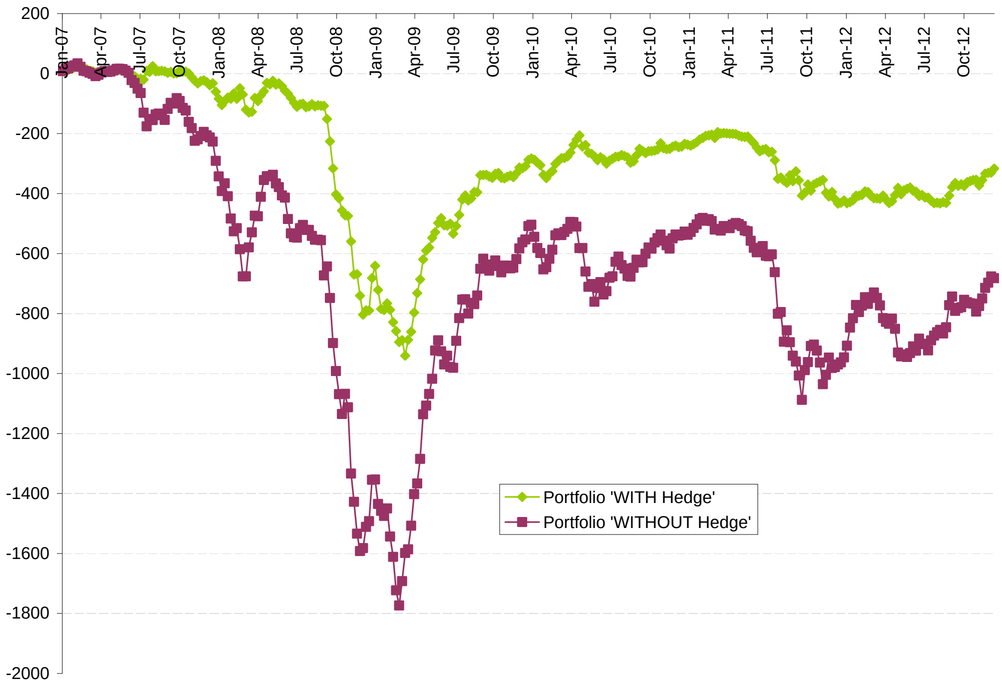


Figure 4.18: Empirical density function for the weekly P&L for the global CDS portfolio. (722 issuers). 2007-2012

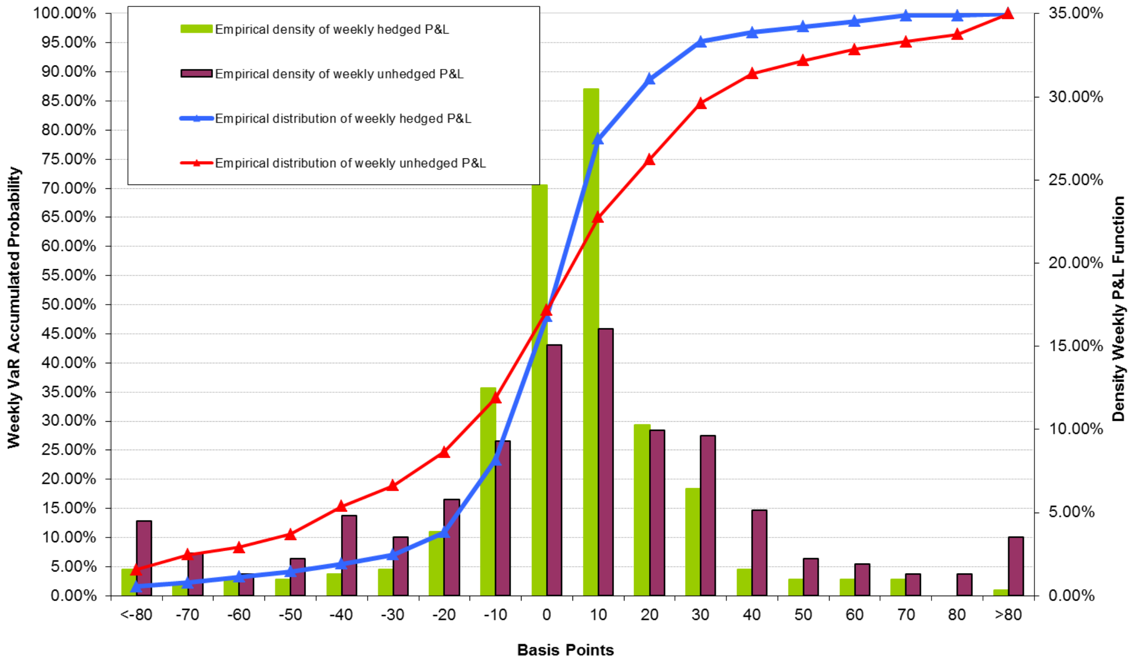
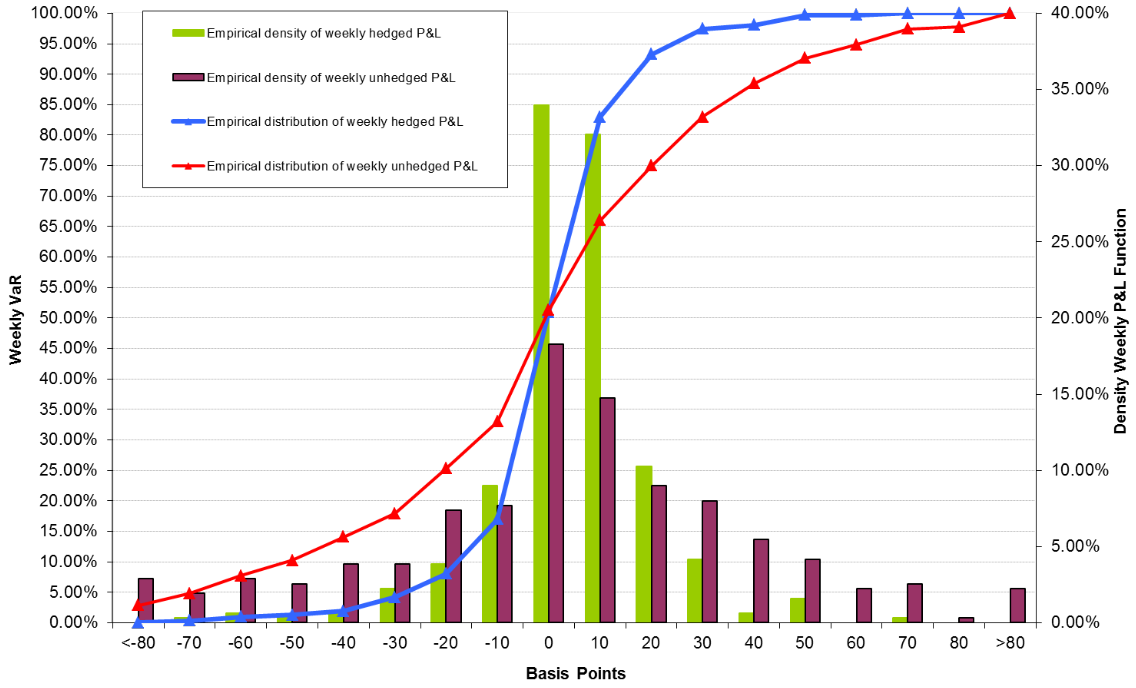


Figure 4.19: Empirical density function for the weekly P&L and the weekly VaR for the European CDS portfolio (iTraxx and HiVol iTraxx as hedges). (246 issuers). 2007-2012



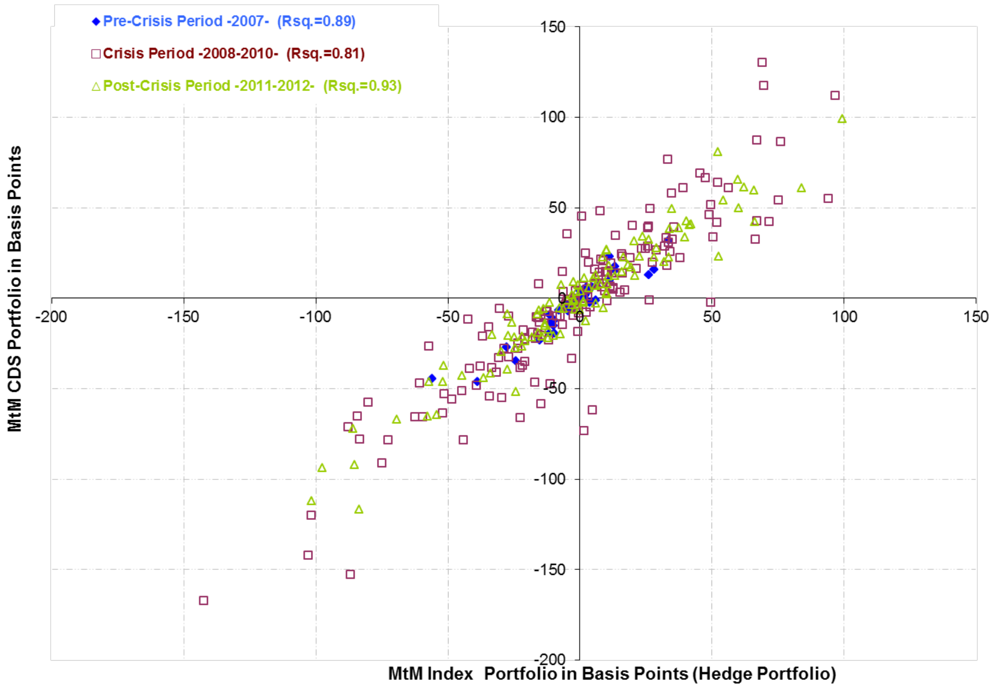
4.5.3 The results of an alternative hedge

Is it possible to increase the effectiveness of the hedge using more credit index to hedge the portfolio?

We are going to try to answer this question using for the European credit portfolio, the iTraxx and the HiVol iTraxx, instead of using just the iTraxx. Again we assume that the liquidity of the two indices is enough to balance our hedge weekly without any entry and removal cost. In this case, the strategy that we are going to use is quite clear, in case that the issuer is an investment grade issuer in a particular week, we use the iTraxx hedge; otherwise we use the HiVol iTraxx. In the case of the North American portfolio, we do the same, but in this case we use as an alternative hedge for the Non-Investment Grade issuers, the High Yield CDX.

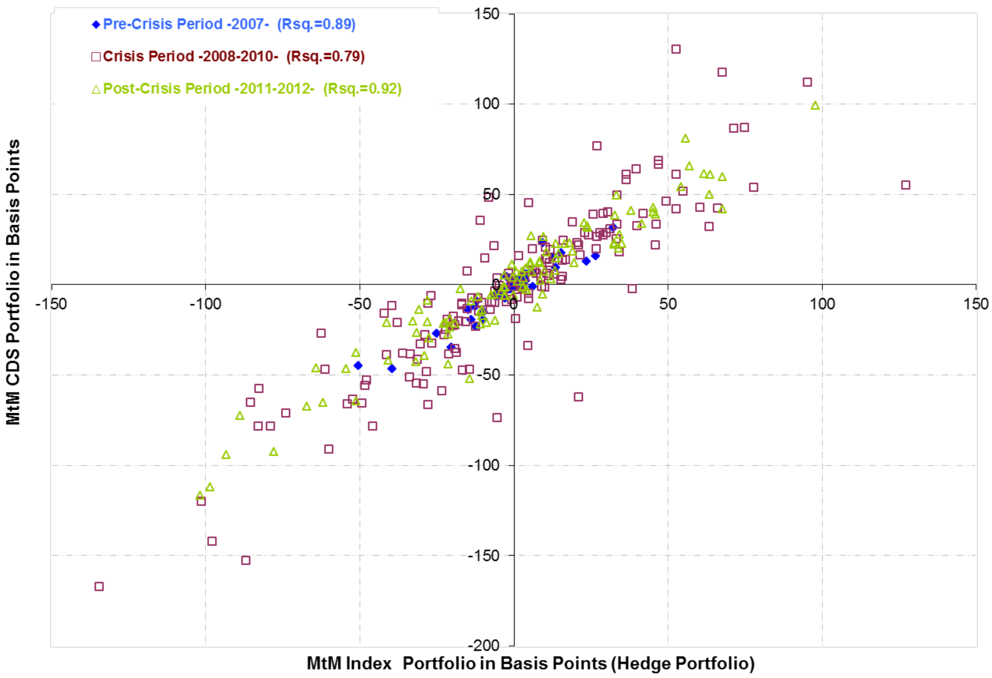
If we compare these results with the European case (Figure 4.9) previously analysed, we observe that we slightly improve the result of the hedge effectiveness. For instance, the probability of having a weekly loss higher than 70 basis points is now 0.32% from the previous 0.96% for the hedged portfolio, reducing the extreme losses that occurred before. On the other hand, if we focus on the density function projected over the right axis, the effectiveness of the hedge (represented by the probability that the mark-to-market of the hedged portfolio is now between zero and ten basis points), is very similar to the previous case of around 65%. Thus, we can conclude that this alternative hedge improves the results, especially the extreme losses occurring for some weeks, but the difference between these two alternative hedges in terms of R-squared is just around 4% in the European portfolio, as shown in Figures 4.19 and 4.20. Finally, we propose the same exercise for the European CDS portfolio again, but using this time the Markit iTraxx Europe Crossover instead of the the HiVol iTraxx, as the first one is more liquid than the second one. The results are practically the same as before, Figure 4.21.

Figure 4.20: Weekly profits and losses for the European CDS and hedge portfolios in basis points. (iTraxx and HiVol iTraxx as hedges).(246 issuers). 2007-2012



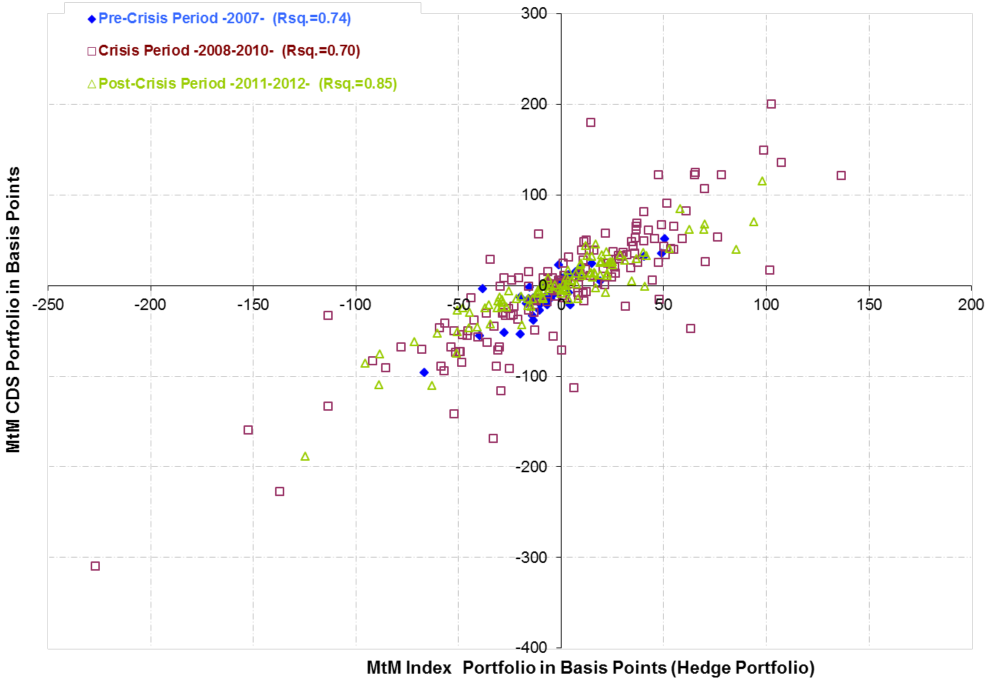
Note: Rsq. = R-squared

Figure 4.21: Weekly profits and losses for the European CDS and hedge portfolios in basis points. (iTraxx and iTraxx Europe Crossover as hedges). (246 issuers). 2007-2012



Note: Rsq. = R-squared

Figure 4.22: Weekly profits and losses for the North American CDS and hedge portfolios in basis points. (CDX and High Yield CDX as hedges). (360 issuers). 2007-2012



Note: Rsq. = R-squared

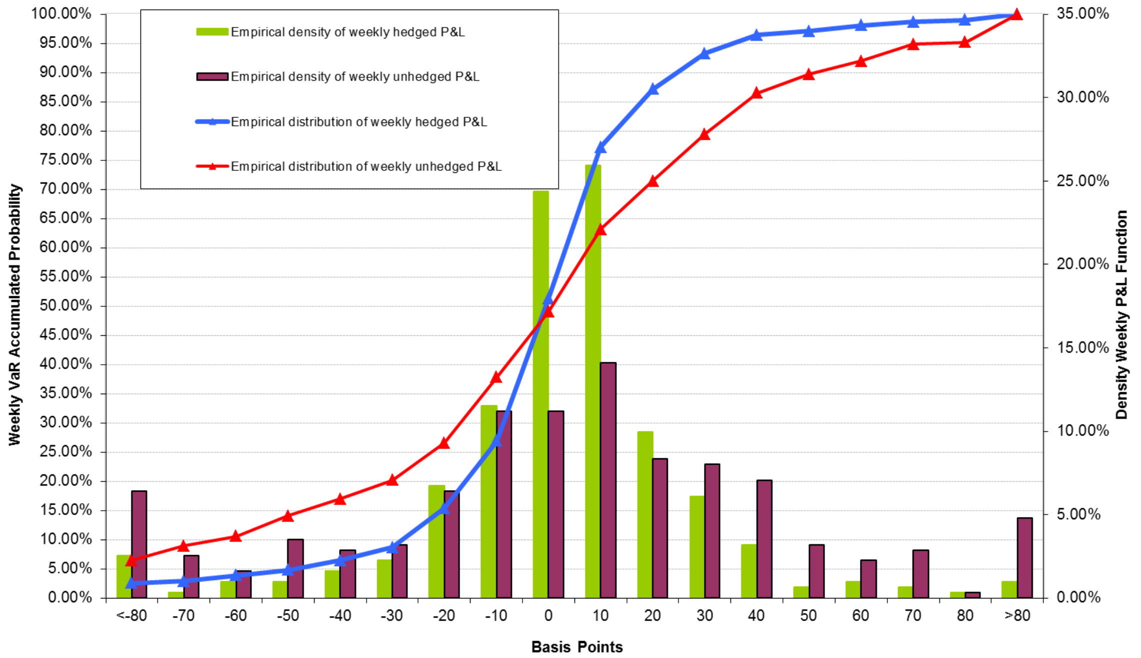
In this last case, we compare the results for the North American portfolio (Figures 4.22 and 4.23). The probability of having a weekly loss higher than 70 basis points is now 2.88% instead of the previous 3.21% (4.12) for the hedged portfolio, slightly reducing again the frequency of the extreme losses that took place in some weeks. In general terms, we observe the same pattern as in the European case. With this alternative strategy, we improve the outcome of the hedge a little, especially the extreme losses in some weeks. In addition, in terms of R-squared, there is also a considerable increase providing a better effectiveness of the hedge with this last hedge alternative. Finally, with these results, it seems clear that it is quite difficult to immunize completely the value of the portfolio.

4.5.4 Daily hedge results

Could we improve the results of the hedge using a daily basis for the hedge?

In this subsection, we analyse the possibility of balancing the hedge daily assuming again that the cost of entry in the market is zero. In this case, we calculate the beta for each issuer with respect to their credit index (without the HiVol iTraxx or High Yield CDX) using a window of 252 daily data. We show the main results for the global portfolio in Figures 4.24, 4.25 and 4.26, which as we initially thought, are poorer in terms of the effectiveness of the hedge compared with the previous cases (see Figures 4.17 and 4.18). In terms of the R-squared, we see an average decrease higher than 10% compared with the previous weekly cases. It seems that the high noise of the credit market during the crisis discouraged the use of daily data, and, even more, when

Figure 4.23: Empirical density function for the weekly P&L and the weekly VaR for the North American CDS portfolio (CDX and High Yield CDX as hedges). (360 issuers). 2007-2012



being aware of the illiquidity of this market. Thus, it is clear that the hedge is less adequate than in the weekly hedge case.

4.5.5 Dynamic conditional correlation beta estimation

Alternatively, we could use an exponential weighted moving average (EWMA) model to estimate the variance of the individual issuer returns, or we can alternatively estimate univariate GARCH models, Novales (2013). In our case, we estimate an EWMA model to estimate volatilities and a DCC GARCH model to estimate the conditional correlation, in order to see see if we improve the results of the hedge that we calculate previously using OLS. In this case to estimate the different beta issuers, we use

$$\mu_i = T^{-1}\sum_{t=1}^{T} r_{it},\ i = 1,2,...n \tag{4.12}$$

$$\sigma^2_{it} = \lambda\sigma^2_{it-1} + (1-\lambda)(r_{it-1} - \mu_i)^2,\ i = 1,2,...n \tag{4.13}$$

where r_{it} is the return on the CDS contract of the issuer i in time t as shown in (3), σ^2_{it} is the variance of the CDS contract of the issuer i in time t, and n is the number of issuers in the sample.

The Dynamic Conditional Correlation (DCC) model uses the standardized returns: $z_{it} = (r_{it} - \mu_i)/\sigma_{it}$, $z_{jt} = (r_{jt} - \mu_j)/\sigma_{jt}$ to generate the auxiliary variables:

Figure 4.24: Accumulated daily profits and losses in basis points for the global CDS portfolio. (722 issuers). 2007-2012

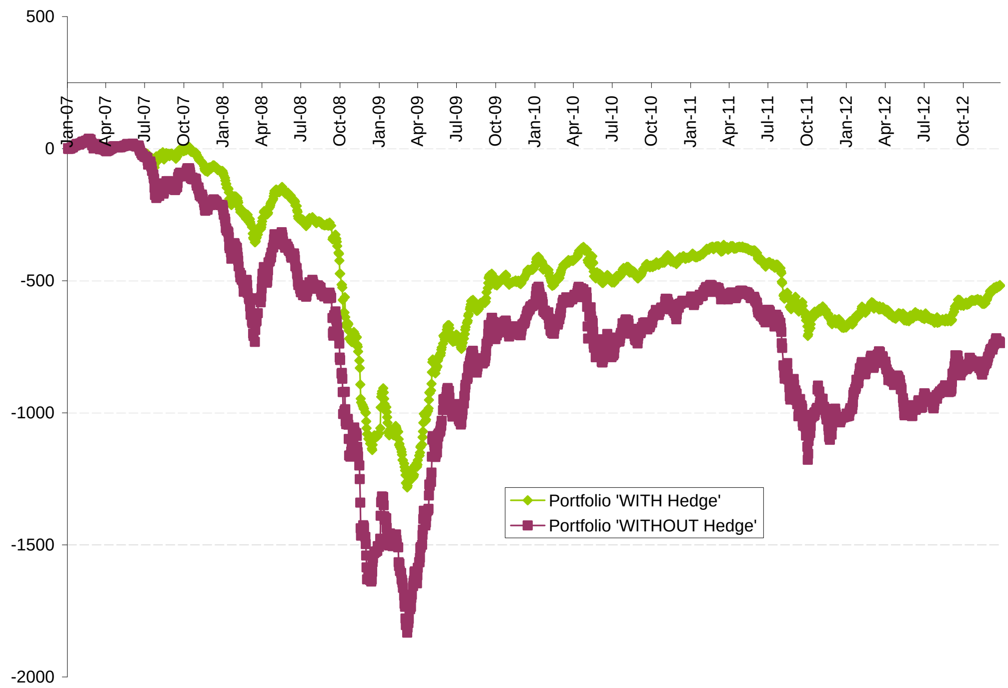


Figure 4.25: Daily empirical density function for the weekly P&L for the global CDS portfolio. (722 issuers). 2007-2012

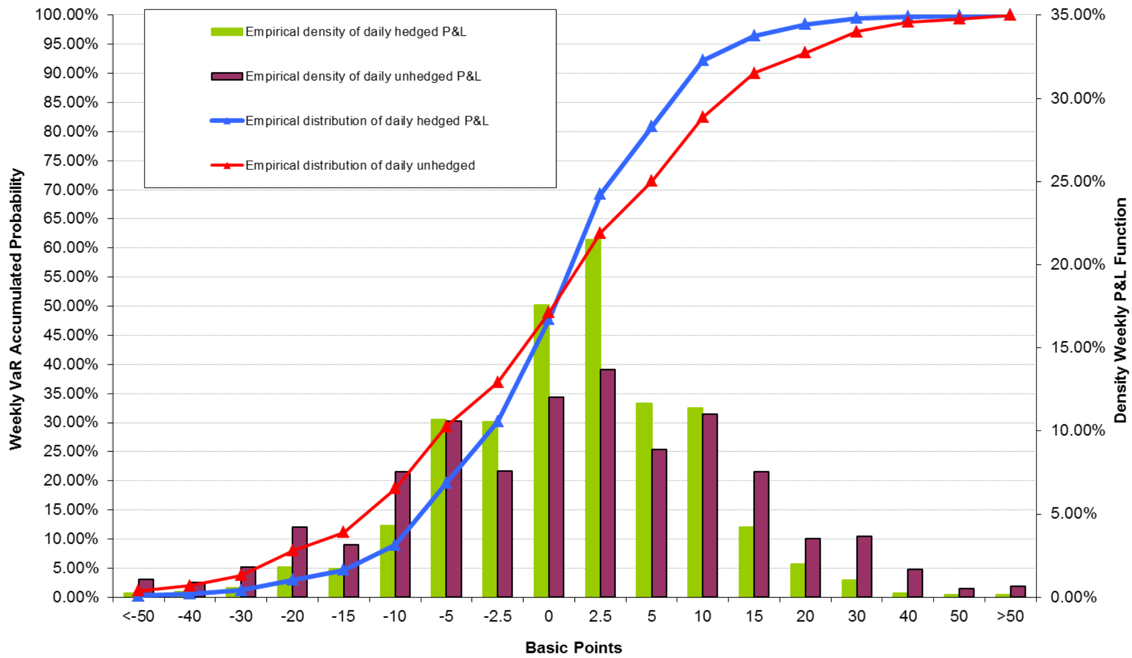
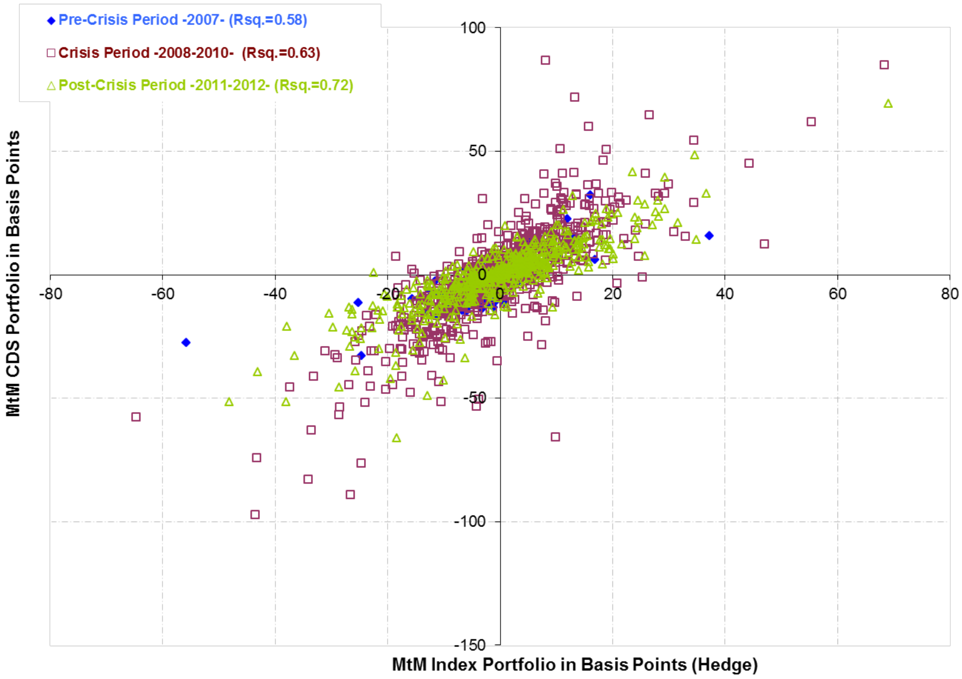


Figure 4.26: Daily profits and losses for the global CDS and hedge portfolios in basis points. (722 issuers). 2007-2012



Note: Rsq. = R-squared

$$q_{ij,t+1} = (1-\lambda)z_{it}z_{jt} + \lambda q_{ij,t}, \forall i,j \tag{4.14}$$

It means that in the case of two variables:

$$q_{11,t+1} = (1-\lambda)z_{1t}^2 + \lambda q_{11,t} \tag{4.15}$$

$$q_{12,t+1} = (1-\lambda)z_{1t}z_{2t} + \lambda q_{12,t} \tag{4.16}$$

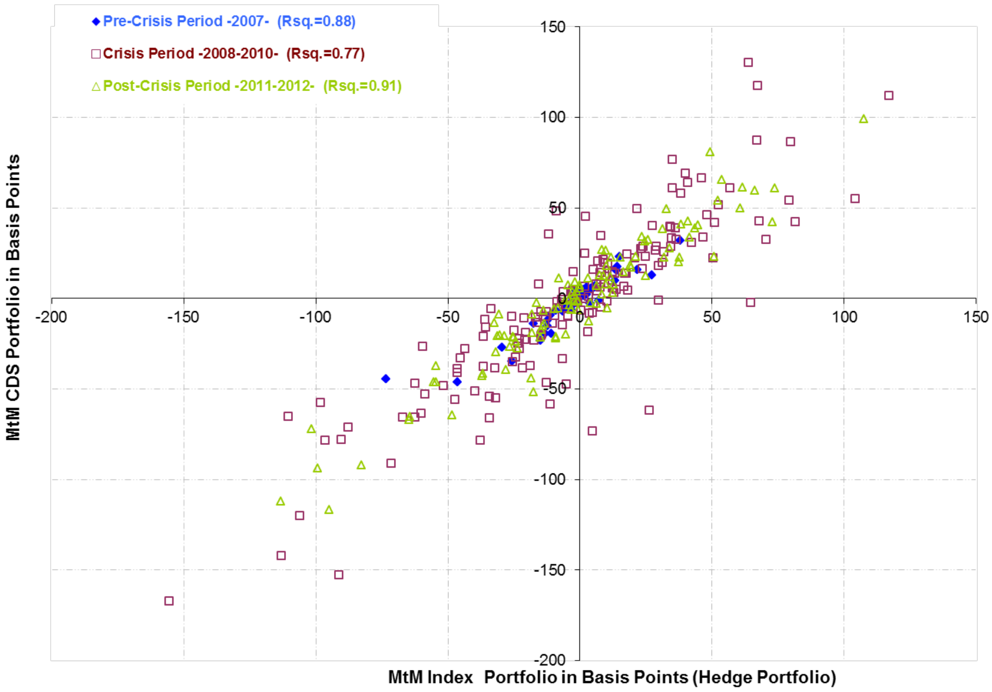
$$q_{22,t+1} = (1-\lambda)z_{2t}^2 + \lambda q_{22,t} \tag{4.17}$$

Thus, the conditional correlation can be estimated as:

$$\rho_{ij,t+1} = \frac{q_{ij,t+1}}{\sqrt{q_{ii,t+1}}\sqrt{q_{jj,t+1}}} \tag{4.18}$$

Finally, we get the covariance and the beta in respect to the market index as:

Figure 4.27: Weekly profits and losses for the European CDS and hedge portfolios in basis points (DCC estimation). (246 issuers). 2007-2012



Note: Rsq. = R-squared

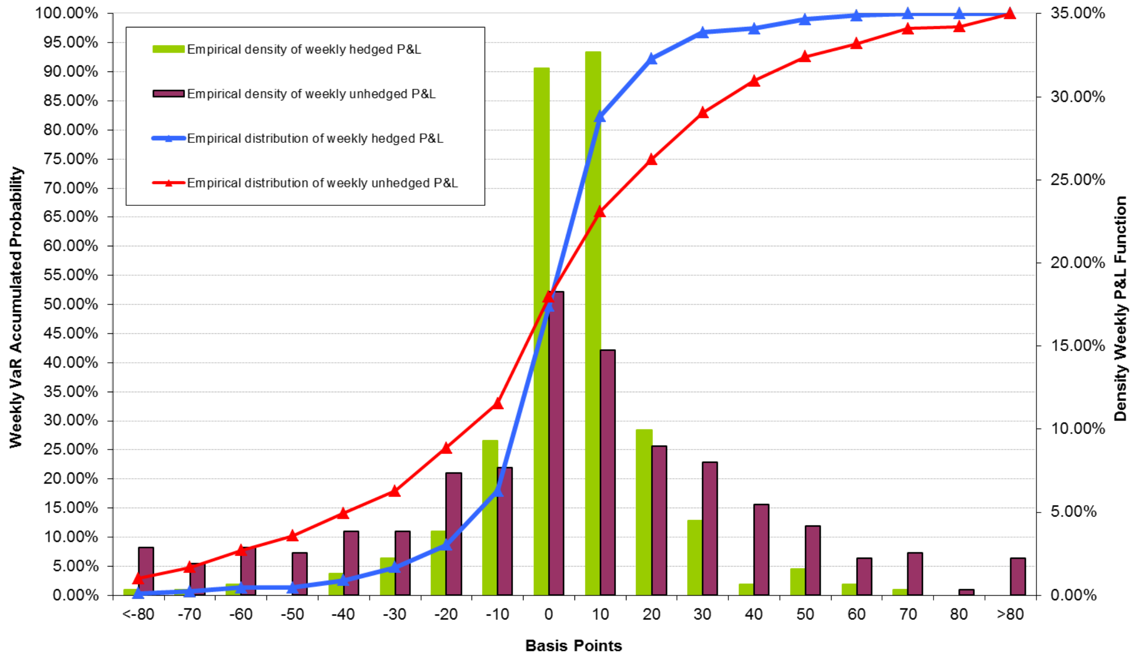
$$Cov_{ij,t+1} = \rho_{ij,t+1}\sqrt{\sigma^2_{1,t+1}\sigma^2_{2,t+1}} \tag{4.19}$$

$$Beta_{i,index,t+1} = \frac{Cov_{i,index,t+1}}{\sigma^2_{index,t+1}} \tag{4.20}$$

In this exercise we use again average weekly data, and the Europe iTraxx as market index for the European portfolio, the CDX as market index for the North American portfolio, and the Japanese iTraxx as market index for the Japanese portfolio. We assume $q_{i0} = 1\,\forall i$, and in the case of q_{ij}, we calculate the average of the product $z_{i,t}z_{index,t}$ of the first 52 observations as the initial value of $q_{i,index,0}$. We establish the parameter $\lambda = 0.94$ based on RiskMetrics, JP Morgan (1996), as we are working with a daily sample that we average weekly. Finally, we also take the standard deviation of the first 52 observations as initial value of σ_{i0}. Therefore, our estimations cover the period from 2007 to 2012 as in the OLS cases.

These results for the European portfolio in Figures 4.27 and 4.28 are quite similar to those estimated by the OLS shown in Figures 4.8 and 4.9 respectively. As a matter of fact, these results are slightly better than those estimated by OLS, as they actually provide a better hedge during the highest volatility period, reducing the probability of getting a higher loss if we compare these graphs with the base case 4.8 and 4.9. There are no considerable differences between these two methods when analysing the result during the whole period of time. In terms of R-squared, the results are very similar with these two alternatives, with an average increase of 1% in favour of the DCC estimation.

Figure 4.28: Empirical density function for the weekly P&L and the weekly VaR for the European CDS portfolio (DCC estimation). (246 issuers). 2007-2012



Finally, we show the results for the global portfolio. These results in Figures 4.29 and 4.30 should be compared with the results shown in Figures 4.17 and 4.18. As in the European case, there are no significant differences between one method and the other, with the exception of some days of extreme volatility where the results provided by the DCC estimation are better than the OLS results. This is logical, as the DCC model estimates an instantaneous variance in time t, weighting more the recent observations, so it is a model that reacts before the OLS model, as the latter weights the entire sample equally to estimate the variance and covariance. This fact is observed very clearly in Figure 4.31, with the median beta sector estimated by the DCC model in contrast with those estimated by OLS, as shown in Figure 4.3.

4.6 Jump-to-Default risk

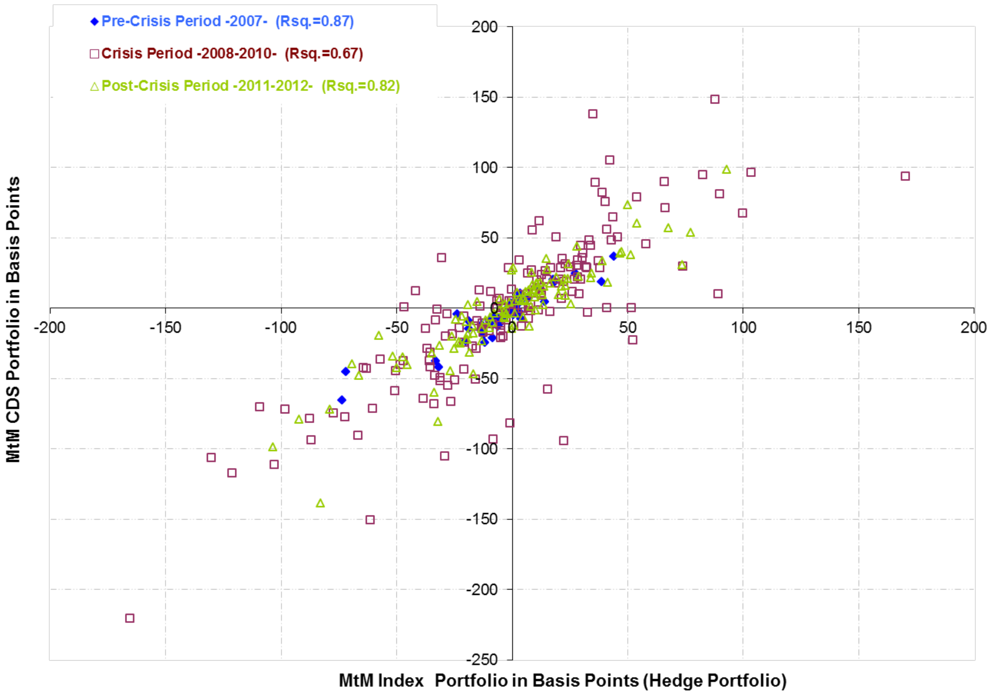
Can we hedge the Jump-to-Default risk from an issuer using a credit index as a hedge? We try to answer this issue.

To introduce this topic we are going to use a report by Bloomberg on 7 December 2011 that highlights the increasing aversion by investors to the lowest rated issuers who had the most exposure to Jump-to-Default (JTD) risk in the recent financial crisis.

"AMR Corp.'s bankruptcy is taking the corporate debt market by surprise, with investors losing 25 percent on bets in junk-bond derivatives that there wouldn't be a jump in defaults this year."

"The failures of AMR, and those of Dynegy Inc. and PMI Group Inc., are driving investors to recalibrate their

Figure 4.29: Weekly profits and losses for the global CDS and hedge portfolios in basis points (DCC estimation). (722 issuers). 2007-2012



Note: Rsq. = R-squared

Figure 4.30: Empirical density function for the weekly P&L and the weekly VaR for the global CDS portfolio (DCC estimation). (722 issuers). 2007-2012

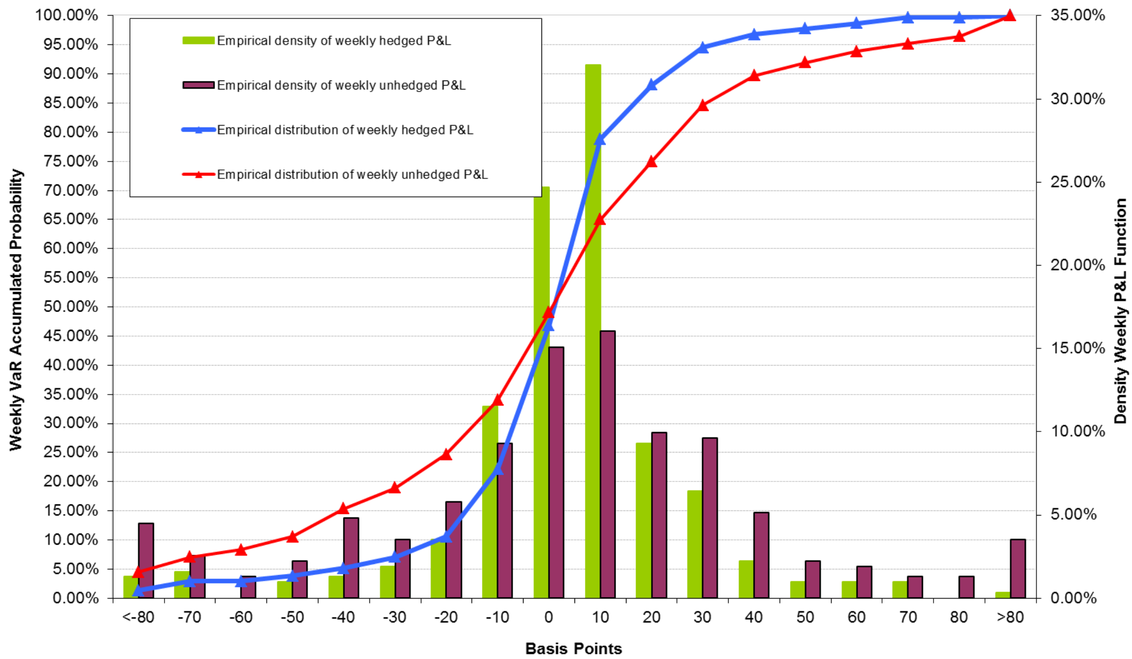
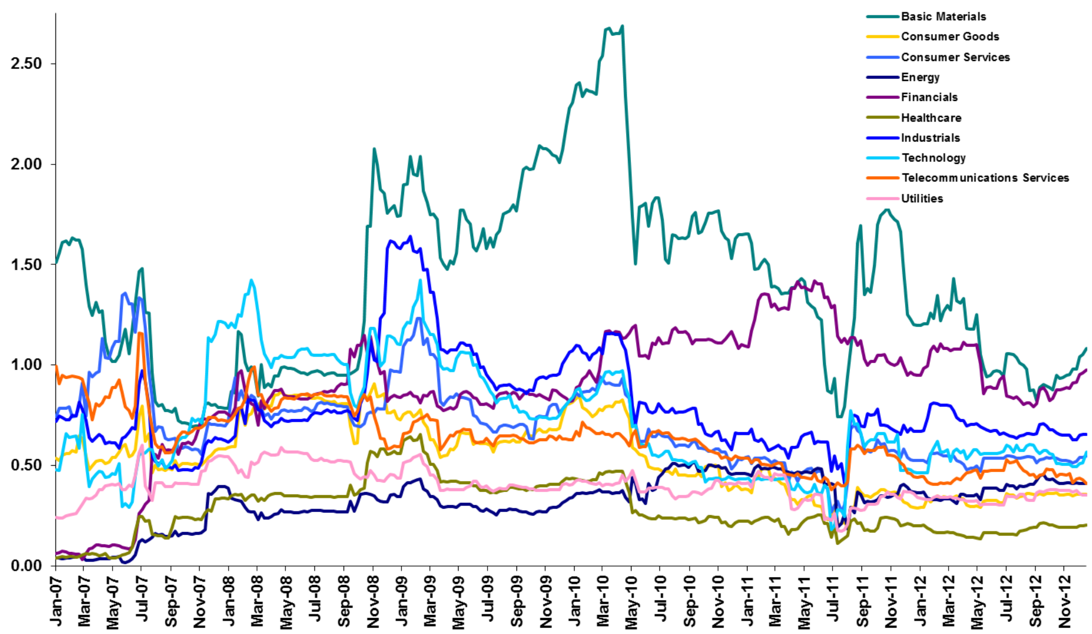


Figure 4.31: Median sector beta DCC estimates for the European CDS portfolio. 2007-2012



expectations for when borrowers may miss debt payments as companies that aren't considered immediate candidates abruptly fail. That's a scenario known among debt traders as Jump-to-Default risk."

"Five-year credit-default swaps on AMR traded at 57 percent upfront on Oct. 26 before soaring to 83 percent the day of the bankruptcy filing, two weeks after talks between the airline and its pilots union stalled, according to broker Phoenix Partners Group."

Jump-to-Default risk could be defined as the risk that an issuer defaults without first showing deterioration in the credit spread. For example let us imagine a default process in which p, the one-day probability of default, follows a random walk (with absorbing barriers at zero and one). Every day, a draw is taken from a uniform (0,1) distribution and if it is less than p, the firm defaults. Now we have a clear separation between spread risk (p moving up or down) and Jump-to-Default (getting a draw that results in default).

From a market point of view, suppose we are long \$16.6 million of 3-year single-name CDS protection on a single name and short \$10 million of 5-year. If this issuer defaults , we make a profit of \$6.6 million, times the loss given default, as the difference between the two contracts. But if the issuer CDS ticks up or down in a parallel shift, the value of our position is unchanged (to a first approximation, anyway, as the DV01 (how much money positions will gain or lose for a 0.01% parallel movement in the yield curve) multiplied by the notional is the same in both contracts. Thus, this position is a pure Jump-to-Default bet. On the other hand, as a possible example, if we would like to make a pure spread bet, we could go long \$10 million of the 3-year and short \$10 million of the 5-year. Now we make a profit if the probability of default goes down, as the risky duration of the 5-year tenor is higher, but in a default scenario we do not have any profits or losses.

Therefore, in our case, using a credit index as a hedge, matching the tenor and the notional, we are partially covering the spread shift in light of the results presented above, but we are still exposed to the Jump-to-Default risk. In case the issuer is part of the credit index, this Jump-to-Default risk will be reduced in proportion to the relative weight of the issuer in the index; otherwise it will be exposed fully to the Jump-to-Default risk without any hedge. This is a concern because delta hedging is partial hedging and its effectiveness is predicated on continually adjusting the hedge ratio, as we did in this chapter. As the issuers worsen their credit quality, we have to adjust the delta hedge ratios, and we have to buy more protection against the deteriorating credit. The goal is to fully hedge against the issuer by the time he defaults. If the credit jumps to default, we will not have adjusted the hedge ratio appropriately, and the defaulted credit exposure will not be fully covered, resulting in a loss.

Finally, there is a second effect that is very difficult to measure: how the jump in the credit index follows a default in a firm which is not included in the index. If we could calibrate a jump model using the information about this hypothetical jump in the credit index, we would be partially covering these jumps to default from issuers that are not in the index, as there is a contagious effect in the credit index spread after a default. Once again, this an open question to analyse in the future.

4.7 Conclusions and open questions

In this chapter we have analysed the empirical basis risk in a CDS portfolio, defining the basis risk as the risk induced by the imperfect correlation between the underlying single CDS contract to be replicated and the credit index contract involved in the dynamic replication strategy (e.g., iTraxx Index). Because of the presence of higher liquidity and lower frictions, financial institutions prefer to hedge their CDSs or CVA by trading in credit indices. If changes in the price of the CDS and the credit index contracts were perfectly correlated, no further risk would be introduced, and one could perfectly offset any gain or loss in the position by dynamically trading in the related index contract. We have shown that even in the case of a large diversified portfolio with more than seven hundred, the basis risk exists, meaning that we cannot fully immunize the value of the portfolio with a hedge based on credit index contracts, assuming implicitly that the idiosyncratic risk is offset among the different issuers in the portfolio.

We evaluate the hedging error of a historical delta-hedging regression strategy, based on weekly observations with different assumptions. Since the regression-based strategy is free of parametric model assumptions about the securities, it is robust to misspecification of models and their parameters. This strategy is adapted to discrete observations of CDS and credit index in the sense that it intends to keep up with the latest information contained in the data, except for some time lag to collect data and to make a reasonable estimate. These results are expected to serve as a benchmark, a lower bound, for evaluating more complex strategies as is normally the case, where we have problems related to maturity mismatch, stochastic exposure or not knowing of the credit spread of the issuer, etc...

We have shown that among the different strategies that we have applied, having accounted for the illiquidity of the market, the best strategy could be the delta hedge weekly estimate by OLS using just the three main credit indices: Europe Main iTraxx, CDX, and Japanese iTraxx. The other alternative strategies just improve these results slightly and they use other indices which are more illiquid, implying normally higher transaction costs. In the case of the DCC estimate, it is a more volatile estimate, with higher entrance and exit costs to adjust the hedge more continuously. However, the DCC estimate could be optimal in a situation with very high volatility, performing almost equally to OLS over the course of an economic cycle.

Another important topic that we see in this chapter is that the Jump-to-Default cannot be ignored as the use of delta hedging is partial hedging and its effectiveness is predicated on continually adjusting the hedge ratio. Therefore, if a single issuer jumped to default, we would not be able to adjust the hedge ratio appropriately, and the defaulted credit exposure would not be fully covered, resulting in a loss. The possibility of calibrating a jump model to evaluate the credit index hedge effectiveness, in case of a Jump-to-Default of an issuer that is not included in that credit index, is an open question.

On the other hand, based on Rama Cont (2006), we should always be aware that the econometric models specify a probability measure P in an attempt to model the historical evolution of market prices, while pricing models use a risk-neutral probability measure Q to specify a pricing rule to relate prices of various instruments in an arbitrage-free manner. If P corresponds to a complete market model, then the pricing rule Q is uniquely defined by P. However, if P corresponds to the more realistic case of an incomplete market model, a multi-factor diffusion model with more factors than tradable assets, as in our case due to the single-name CDS illiquidity, then the knowledge of P does not determine the pricing rule Q in a unique way. Therefore, even if P is known with certainty we still face uncertainty in the choice of the pricing model Q. Thus, the concept of model uncertainty in the context of pricing goes beyond the traditional uncertainty of the evolution of the underlying asset. This is the uncertainty of pricing rules. Finally, it is interesting to comment on the difference between the liquid traded assets and the illiquid asset. In the first ones as the credit indices or main stocks, the price is determined by supply and demand in the market,[7] pricing models are therefore not used to price those assets. However, the price of an illiquid asset is normally computed using a pricing model that should be consistent with the observed market prices of the traded assets in order to avoid arbitrage.

Hence, it seems clear in the price of derivatives that we should charge some basis points in terms of unhedgeable risk, as in this case. For instance, a good place to start would be to measure the loss in basis points to include as an extra charge in the price of derivatives depending on the proxy portfolio and adjusted by maturity. From the point of view of the regulators, we could think about using a historical percentile to have a lower bound of the basis risk that should be added in terms of capital, and monitor this risk among the financial institutions in order to prevent future problems.

As an open question, it would be interesting to carry out this study with other assumptions as with a transaction cost different from 0, with stochastic exposure, or using an alternative strategy involving more credit

[7] See also Derman (2013)

indices. Finally, it would be interesting to try to hedge the credit portfolio with credit and equity indices since the latter are highly liquid assets and, consequently, this strategy could reduce the hedge error shown in this study.

Chapter 5

Forward-looking asset correlations in the estimation of capital for a loan portfolio

5.1 Motivation

In this chapter we intend to answer the following questions:

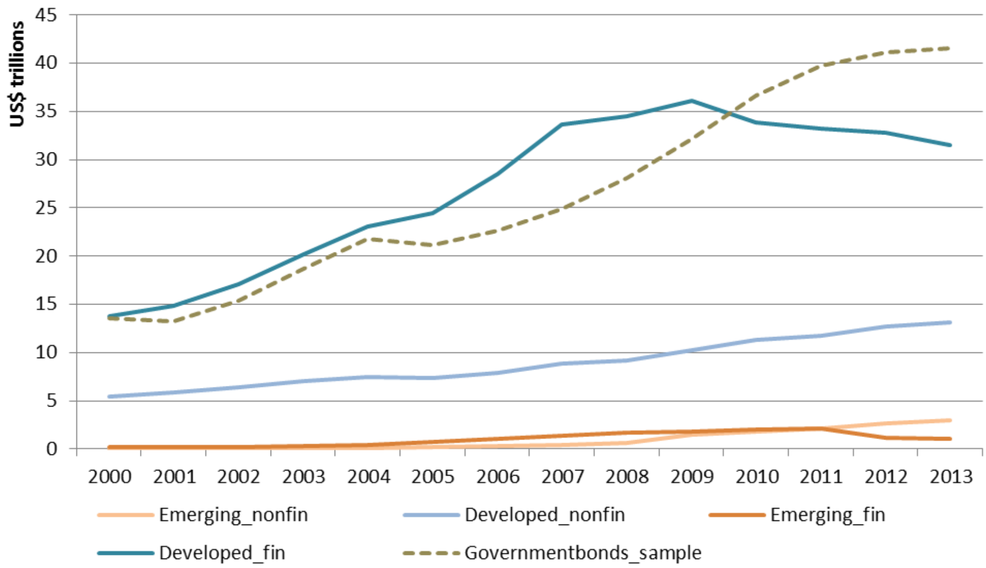
Has the credit market anticipated the crisis before the regulators? Was there any information in the market showing signs of the current credit crisis? Did the financial system ignore them? Is the loan portfolio of the financial entities insensitive to the CDS market?

The correlation among a firm's assets is one of the most important factors when calculating the capital needed to face the unexpected losses of a credit portfolio under the Internal Ratings-Based approach (IRB) in Basel II [see Basel Committee (2006)] and for many of the credit models in the financial industry. Unfortunately, asset correlation is not directly observable in the market; thus, we are forced to use different methods in order to estimate asset correlation, McGinty et al. (2004).

The approach most often used to determine economic capital is the Merton model (also known as "structural model"). The principal advantage of this method is the strong economic rationale that explains the firm's default. This default occurs when the asset value is below the debt value. This approach has been widely used by the financial community to estimate the economic capital of a loan portfolio. Nowadays, this approach is the base for the current Basel II IRB model to calculate the loan portfolio capital needs for those entities that use advanced models. As we mentioned before, asset correlation is vital for the estimation of the economic capital. In Basel II, the regulator establishes the correlation as a deterministic function of the probability of default.

In 2007, Dullmann et al. (2007) with a dataset for 1998-2004 conducted some hypothesis tests against the

Figure 5.1: Bond and CDS notional outstanding



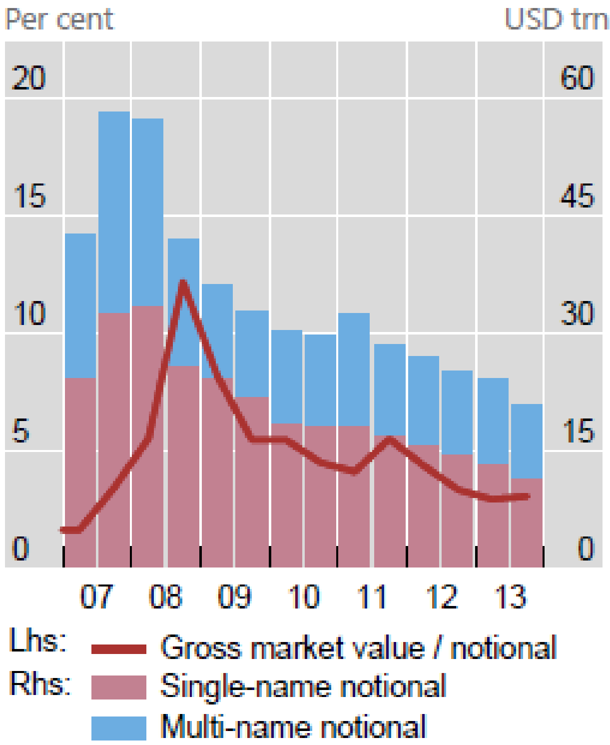
Sources: IOSCO (2014)

regulator's results. Instead of using a function for asset correlation depending on the probability of default, he used various assumptions for asset correlation. Those results show that the different proposed models and the Basel II IRB approach produce a similar outcome. The main reason for this is that the results from Basel II IRB model were previously calibrated, and both use the same KMV database and a very similar time frame [see Crosbie (1999) and Crosbie (2003) for more details]. However, since the year 2000, we have experienced a big increase in the CDS market (Figure IOSCO (2012)) becoming one of the prime credit markets during the last decade. Figure 5.1 represents the volume of the bond market (Figure IOSCO (2014)) for each subcategory, and Figure 5.2 shows the different notional outstanding for each CDS subcategory.

The economic capital estimated by CDS spreads might be a very useful alternative for portfolio managers. These estimates could provide us with relevant information about future systemic adverse shocks as well as an alternative tool for risk management and asset allocation. Therefore, we propose a similar Dullmann study but using CDS data, with more industries, eleven industries instead of the six used by Dullmann, and for a more recent period, 2006-2012, where we could distinguish among the pre-crisis period, the global crisis period, and the post-crisis period. Finally, we could compare these estimations against Basel II to put these figures in the context of the regulatory requirement capital.

This chapter is divided into eight sections: In Section 5.2 we introduce the default correlations, and then in Section 5.3 we present the proposed methodology. In the Section 5.4 we detail the dataset that we have used, and the different hypotheses employed. In Section 5.5 we detail the framework for the analysis. In Section 5.6 we focus on the results of these methodologies, continuing with some critical issues in Basel II in Section 5.7. And finally we present the main conclusions and open questions in Section 5.8.

Figure 5.2: CDS notional outstanding by single-name and multi-name



Sources: Basel Committee (2014).

5.2 Introduction default correlations

In this section, we explain why the use of structural theoretical models is indispensable for the evaluation of the risk of default correlation. Firstly, there are several sources for assessing of default correlation, although none is perfect:

- **Actual rating and defaults events**

In theory, this is the most obvious source of the relationship between default for modelling purposes, though it is not generally used in practice. The problem with this approach is that the defaults are very rare events, so in order to obtain a statistically significant sample of data points, a very long history is required. Therefore, the economic circumstances of a very remote past may not be relevant today.

- **Credit spreads**

Credit spreads contain continuous information about the default risk of traded bonds, for instance, the bond price may be influenced by illiquidity factors. Another important limitation is that there is not theoretical justification for the direct link between credit spread correlation and default correlation. For example, two obligors could have a low credit spread correlation up to defaults, but they still have very high default correlation. (In our approach we will use structural models but using the available credit spread information).

- **Equity correlations**

It is not unusual to suggest that credit and equity are related. Robert Merton first published his framework modelling the relationship, later known as the structural models, in 1974. These structural models aim to provide an explicit relationship among default risk and the capital structure. Equity returns are generally used as a proxy for asset returns for the structural models. Therefore the advantage of using equity data is that there is a good history of company prices. The main limitation of this approach is that the link between equity, debt, and asset (leverage) is not constant, and difficult to measure and judge. For example, two firms can be highly correlated from the point of view of the equity returns, and at the same time, they can exhibit a low asset correlation.

The most important reason for the use of structural models is the fact that the specifications of full joint probabilities is simply too complex. There are 2^N joint default event for N obligors. For a loan portfolio with twenty counterparties or more it is impossible to enumerate these probabilities.

5.3 Methodology

In this section, we present the different models (Basel II IRB model, market model, sector model, individual sector model, and sector market model) that we are going to use to determine the value at risk (VaR) under different assumptions. In the last part, we detail how we estimate the asset correlation for the different models from the CDS market.

To model the possibility of default, we propose the use of the Merton Model using the information from the CDS market. We consider that each firm receives a single loan (Vasicek, 2002). The loan defaults at maturity T, if the borrower's asset falls below the contractual value of its debts D_i. Let us assume that the value of firm's assets follow a geometric Brownian motion as:

$$dV_i(t) = \mu_i V_i(t)dt + \sigma_i V_i(t)dW_{i,t},\ i = 1,2,...n \tag{5.1}$$

Where μ_i represents the expected growth rate of the assets for the firm i, σ_i is the volatility of asset value, $W_{i,t}$ is a variable following a Wiener process, and n is the number of firms. We assume μ_i and σ_i are constant. Applying Ito's lemma to the logarithmic transformation, we have:

$$dlnV_i(t) = \left(\mu_i - \frac{\sigma_i^2}{2}\right)dt + \sigma_i dW_{i,t} \tag{5.2}$$

And hence, starting from $V_i(0)$, the value of firm's i assets at each point in time is:

$$lnV_i(t) = lnV_i(0) + \left(\mu_i - \frac{\sigma_i^2}{2}\right)t + \sigma_i\sqrt{t}dW_{i,t} \tag{5.3}$$

We denote the current time as $t = 0$, and we define the Modified Distance to Default of firm i [following Hull et al. (2010)] at the current time period as:

$$MDD_{i,0} = \frac{lnV_i(0) - lnD_i}{\sigma_i} \tag{5.4}$$

Similarly, the Modified Distance to Default can be defined at any point in time t as:

$$MDD_{i,t} = \frac{lnV_i(t) - lnD_i}{\sigma_i} \tag{5.5}$$

Where D_i denotes the contractual value of its debt. As the formula suggests, $MDD_{i,0}$ is the logarithm of the leverage ratio, which by definition is equal to the value of the assets of firm i, divided by the contractual value of its debts $(V_i(0)/D_i)$, and scaled by the volatility σ_i. Since $MDD_{i,t} = f(V(_i(t))$, with $f(x) = \frac{lnx - lnD_i}{\sigma_i}$, so that: $f^{'}(x) = \frac{1}{\sigma_i}\frac{1}{V_i(t)}$, $f^{''}(x) = -\frac{1}{\sigma_i}\frac{1}{V_i(t)^2}$. Therefore, applying Ito's Lemma, we have:

$$\begin{gathered} dMDD_{i,t} = \left(\sigma_{i,t} f^{'}(V_i(t))\right) dW_{i,t} + \left(\mu_{i,t} f^{'}(V_i(t)) + \tfrac{1}{2}\sigma_{i,t}^2 f^{''}(V_i(t))\right) dt = \\ = \sigma_i V_i(t) \tfrac{1}{\sigma_i}\tfrac{1}{V_i(t)} dW_{i,t} + \left(\mu_i V_i(t)\tfrac{1}{\sigma_i}\tfrac{1}{V_i(t)} - \tfrac{1}{2}\sigma_i^2 V_i(t)^2 \tfrac{1}{\sigma_i}\tfrac{1}{V_i(t)^2}\right) dt = \\ dW_{i,t} + \left(\mu_i \tfrac{1}{\sigma_i} - \tfrac{1}{2}\sigma_i\right) dt \end{gathered} \tag{5.6}$$

Hence $dMDD_{i,t}$ has a drift $\gamma_i = \frac{(\mu_i - \sigma_i^2/2)}{\sigma_i}$ and a unit variance.
Firm i defaults at time t in the future if $MDD_{i,t} < 0$, so the probability of default at time T is:

$$\begin{gathered} PD_{i,T} = P(MDD_{i,T} < 0) = P\left(MDD_{i,0} + \int_0^T dMDD_{i,t} dt < 0\right) = \\ = P\left(MDD_{i,0} + \frac{(\mu_i - \sigma_i^2/2)}{\sigma_i} T + \sqrt{T} dW_{i,T} < 0\right) = P\left(dW_{i,T} < -\frac{1}{\sqrt{T}} MDD_{i,0} - \frac{(\mu_i - \sigma_i^2/2)}{\sigma_i\sqrt{T}} T\right) = \\ = P\left(dW_{i,T} < -\frac{1}{\sqrt{T}} MDD_{i,0} - \gamma_i\sqrt{T}\right) \end{gathered} \tag{5.7}$$

And if we assume that the return on firm's assets has zero mean and consider $T = 1$ year, we have:

$$PD_{i,1} = P\left(dW_{i,1} < -MDD_{i,0}\right) \tag{5.8}$$

so that, firm i defaults if $dW_{i,1} < -MDD_{i,0}$, that is, whenever:

$$dW_{i,1} < N^{-1}(PD_{i,1}) \tag{5.9}$$

Which is the condition we will use below when we estimate VaR by Monte Carlo simulations.

Where N^{-1} denotes the inverse of the cumulative distribution function of a $N(0,1)$ random variable.

Since $dW_{i,1}$ has a $N(0,1)$ distribution, then the previous argument provides us with a way to estimate $MDD_{i,0}$ from $PD_{i,1}$ estimates. Indeed, from ecuation (5.9) we have:

$$MDD_{i,0} = -N^{-1}(PD_{i,1}) \Leftrightarrow MDD_{i,0} = 1 - N^{-1}(PD_{i,1}) \tag{5.10}$$

Which is the condition we will use below to estimate correlation parameters.

Default can equivalently be defined in terms of the value of firm i assets. Firm i defaults whenever the value of its assets is below the value of its debt, so that the probability of default at time T can be written:

$$\begin{aligned} PD_{i,T} &= P(ln(V_i(T) < lnD_i) = P(ln(V_i(0) + (\mu_i - \sigma_i^2/2)T + \sigma_i\sqrt{T}dW_i < lnD_i) = \\ &= P\left(dW_{i,T} < -\frac{1}{\sqrt{T}}MDD_{i,0} - \frac{(\mu_i-\sigma_i^2/2)}{\sigma_i\sqrt{T}}T\right) \end{aligned} \tag{5.11}$$

the same condition we obtained above. It is easy to show that the same default condition as ecuation (5.9) can be obtained by using ecuation (5.2) to substitute for $lnV_i(1)$:

$$\begin{aligned} PD_{i,1} &= P(ln(V_i(1) < lnD_i) = P(\Delta ln(V_i(1) < -MDD_{i,0}\sigma_i) \\ &= P\left[\left(\frac{(\mu_i-\sigma_i^2/2)}{\sigma_i}\right) + \sigma_i dW_{i,1} < -MDD_{i,0}\sigma_i\right] = \\ &= P\left(dW_{i,1} < -MDD_{i,0} - \frac{(\mu_i-\sigma_i^2/2)}{\sigma_i}\right) \end{aligned} \tag{5.12}$$

so that under the assumption $\gamma_i = 0$ [based on Tarashev and Zhu (2008)] default arises when $\frac{\Delta lnV_i(1)}{\sigma_i} < -MDD_{i,0}$, that is whenever:

$$\frac{\Delta lnV_i(1)}{\sigma_i} < N^{-1}(PD_{i,1}) \tag{5.13}$$

So that we can simulate values for either $dW_{i,T}$ or a standardized version of $\Delta lnV_i(T)$, to be compared with $N^{-1}(PD_{i,T})$.

To compute this estimate of $MDD_{i,0}$, we first need to estimate default probabilities, $PD_{i,1}$, from CDS data, as: $PD_{i,1} \approx 1 - e^{\frac{-CDS_i^{5y}}{1-R_i}}$ where R_i is the recovery. The term $e^{\frac{-CDS_i^{5y}}{1-R_i}}$ is equivalent to $e^{-h\cdot 1}$ that appears in equation (2.12) in Chapter 2. Note the hazard rate, h, is approximated by $h = \frac{CDS_i^{5y}}{(1-R_i)}$. This approximation is standard among practitioners and is known as the credit triangle that relates the spreads, default probabilities, and recovery rates. This approximation assumes independence between the exogenous default process and the risk-free rates. In addition to this, if the premium leg were paid continuously, the present value of the premium leg of a CDS would be, $PV_{Premium,continuous} = NCDS\int_0^T P(t)Q(t)dt$ where N, CDS, $P(t)$, $Q(t)$ are the notional, the CDS spread, the discount factor and the probability of survival at time t, respectively. On the other hand, the present value of the protection leg of a CDS is $PV_{ProtecionLeg} = -N(1-R)\int_0^T P(t)\frac{dQ(t)}{dt}dt = -N(1-R)\int_0^T P(t)dQ(t)$, where $P(t)$, $dQ(t)$ are the discount factor and the infinitesimal probability of a default at time t, and R is the recovery. Therefore, the par ("fair") CDS spread CDS_p ignoring any accrued interest would be given by: $CDS_p = -1(1-R)\frac{\int_0^T P(t)Q(t)dt}{\int_0^T P(t)dQ(t)}$. Under the further assumption that the hazard rate is constant at a level, h, this becomes the credit triangle relationship: $CDS_p = (1-R)h\frac{\int_0^T P(t)e^{-ht}dt}{\int_0^T P(t)e^{-ht}dt} \leftrightarrow h = \frac{CDS_p}{1-R}$ [see for more details White (2013)]. Note also that we use the 5-year CDS spread instead of the 1-year CDS spread because of their representativeness.

Once we have $PD_{i,1}$, estimates, Modified Distance to default is estimated as in equation (5.10). Then, we estimate sector (X_s) and global risk factors (X) as the average of $MDD_{i,0}$ estimates over the appropriate set of firms (the set of firms in a given sector, or the whole set of firms in the sample).

Let us define a market index, MI for all the companies contained in this study, which will play the role of the common factor X in equation (5.20), which was a global index for the whole economy, as:

$$MI = \frac{\sum_{i=1}^{n} MDD_i}{n} \tag{5.14}$$

where n is the number of issuers in the market.

Thus we estimate equation (5.20) as:

$$r_i = Corr(MDD_i, MI) \tag{5.15}$$

Equally, we establish the sector index,MSI_s, for the sector s as:

$$MSI_s = \frac{\sum_{i=1}^{n_s} MDD_i}{n_s} \;\forall i \in s \tag{5.16}$$

where n_s is the number of issuers in the sector s. And we proceed to estimate the other models similarly. For instance, ω_{sz} is estimated by $Corr(MSI_s, MSI_z)$.

Finally, we get the intra-sector correlation, r_{i_s}, for each issuer i in sector s as:

$$r_{i_s} = Corr(MDD_i, MSI_s) \tag{5.17}$$

In other words, we start by defining a global index for a particular sector as the sectorial factor, and then we estimate the asset correlation of each issuer j in that sector with the credit sector index in its factor.

To estimate these indices, we follow the next steps:

1. We average MDD_i weekly in order to avoid the excessive daily market noise of the analysed period. Therefore, we now have 365 weekly MDD_i for each issuer.

2. We calculate the sector index,MSI_s, for each sector s as in (5.16) on a weekly basis.

3. We obtain the market index, MI, applying equation (5.14) on a weekly basis.

4. In the next step, we get the time series of weekly log returns for the individual firms, sector indices, and the market index.

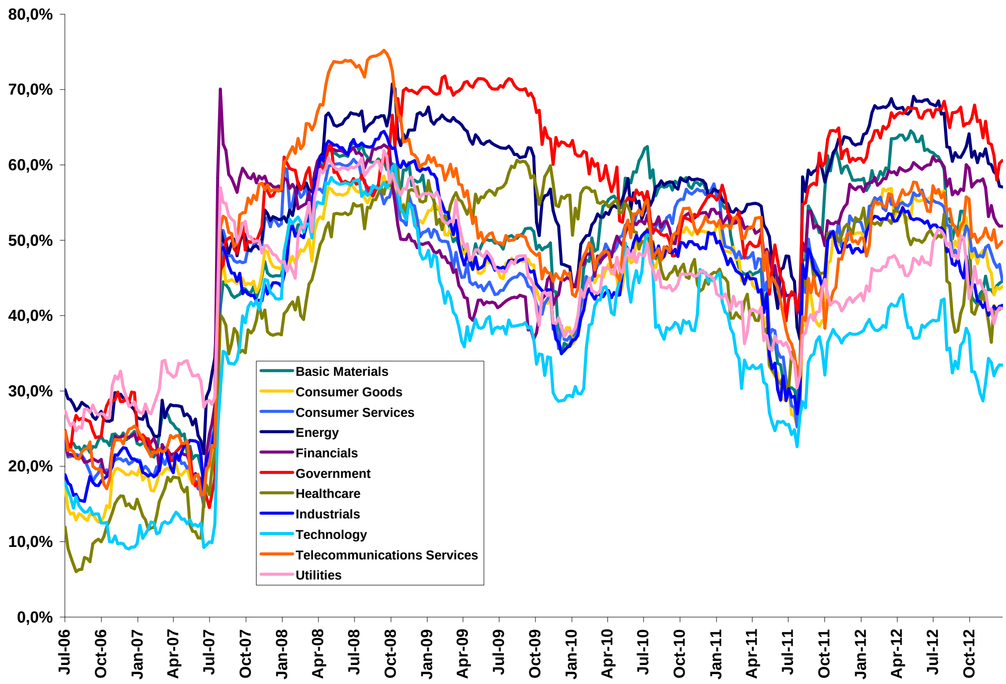
5. We calculate the correlation, r_i, between each firm i and the market as in (5.15) , using a time window of 52 observations, a year. Therefore, we finally have 313 weekly correlation observations for the portfolio composed by 881 issuers. Thus the results cover the period from 2007 to 2012.[1]

6. We calculate the intra-sector correlation, r_{i_s}, for each issuer i in sector s as in (5.17), using a time window of 52 observations, using a weekly logarithmic return.

7. In addition to this, we get the inter-sector correlation ω_{sj} estimated by the sample correlation of index returns for the s and j sector with the same time window.

Finally, the Figure 5.3 shows the median intra-sector asset correlation with the different sectors. Finally, Figures 5.4 and 5.5 display the inter-sector correlation for the financial sector, and for the utilities sector.

Figure 5.3: Median intra-sector asset correlation. (2006-2012)



[1] In order to increase the period analysed, we really work with the dataset from mid-2005 to 2012. During the six months between mid-2005 to 2006, we have an 840-issuer portfolio instead of the 881 issuers. In that case to estimate the correlation of these assets for these six months we use the proxy of the median sector correlation.

Figure 5.4: Inter-sector correlation with the financial sector. (2006-2012)

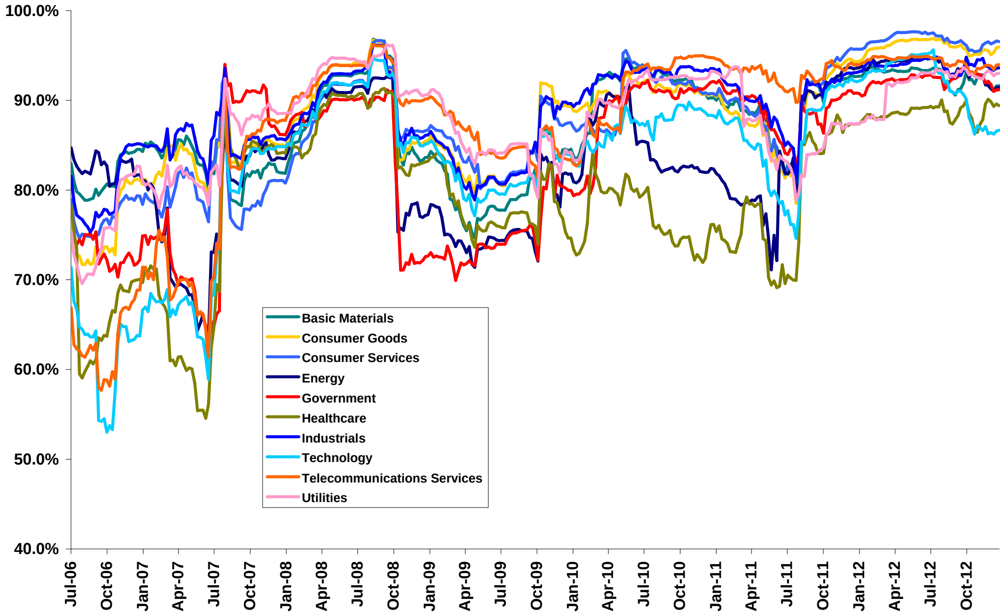
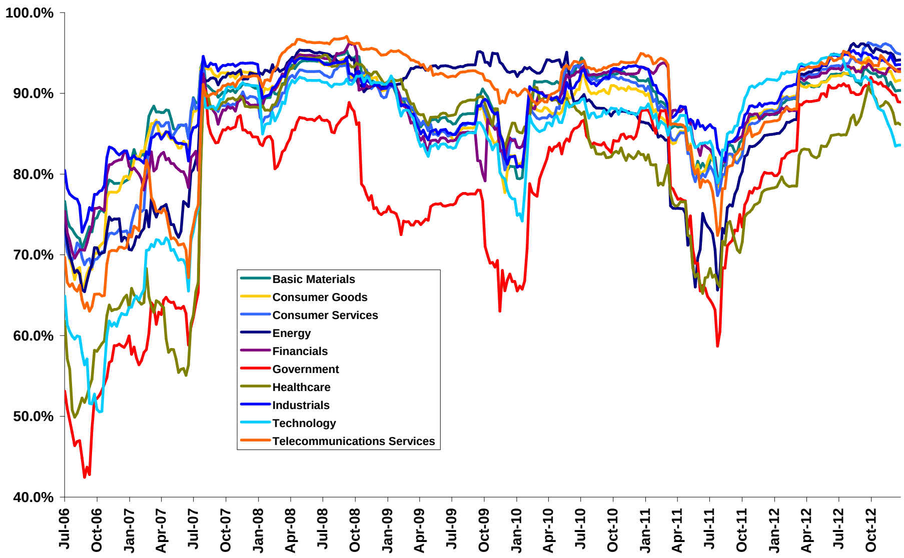


Figure 5.5: Inter-sector correlation with the utilities sector. (2006-2012)



5.3.1 Basel II IRB model (one-factor model)

As we have mentioned above the default happens when a continuous variable dW_i falls below the contractual value of its debts, thus, the default barrier for borrower is given by $N^{-1}(PD_i)$ where $N^{-1}(\cdot)$ is the inverse of the cumulative normal distribution function.

To capture the interactions among firms dW_i is decomposed into two factors, a common systematic factor, X, and a specific factor, ξ_i, resulting:

$$dW_i = r_i X + \sqrt{1-r_i^2}\xi_i \tag{5.18}$$

where X, ξ_1,ξ_2......,ξ_n are mutually independent standard normal variables. Equations (5.3) and (5.18) represent the standard one-factor model. The r_i parameters are related to the correlations among firms' assets. Indeed, asset correlations are generated by the dependence of the value of assets of each borrower on the general state of the economy. All borrowers are linked to each other by the single risk factor X. This factor X can be interpreted as a common factor for the assets in the portfolio, such as a global economic index over the time period $(0, T)$. On the other hand, the $\sqrt{1-r_i^2}\xi_i$ represents the company specific risk. This model is the essence of Basel II, establishing r_i^2 as a function of the probability of default, PD, of the firm i through the function:

$$r_{PD_i}^2 = 0.24 - 0.12 \cdot (1 - \exp^{-50 \cdot PD_i}) \tag{5.19}$$

5.3.2 Market model (one-factor model)

The market model is specified by (5.3) with X being again the same for all the issuers, since it is also a one-factor model. The decomposition of the standardised asset returns is also as in equation (5.18). The difference between this model and the Basel II IRB model is that the coefficient r_i is specific for each issuer i instead of being as a function of the probability of default as in equation (5.19). This parameter r_i is estimated by the sample correlation between the value of firm's asset returns and the market index returns. This makes sense as:

$$Cov\left(dW_i, X\right) = Cov(r_i X + \sqrt{1-r_i^2}\xi_i, X) = r_i Var(X) = r_i = Corr\left(dW_i, X\right) \tag{5.20}$$

where the last equality is based on the unit variance of the two variables. Note that we are assuming that $Cov(\xi_i, X) = 0 \forall i$, a standard assumption.

5.3.3 Sector market model (one-factor model)

In the market model factor X is the same for all the issuers, as it is a one-factor model, but the r_i parameter is specific of each issuer i. This parameter r_i is estimated in that model by the correlation between the firm and the market index returns. However, an alternative possibility would be the use of the market model factor with the next assumption :

$$r_s = med_i\left[Corr\left(dW_i, X\right)\right] \tag{5.21}$$

In this case, we use the same correlation r_s for all the issuers placed in the sector s, instead of using individual correlation r_i for each i issuer. r_s parameter is estimated by the (positive) square root of the median of all intra-sector asset correlations in the sample. We refer to this alternative as the sector market model in this study.

5.3.4 Sector model (multi-factor model)

In the sector model, we consider a different factor for each sector, with the number of sectors and factors are equal to N, and we assign each firm to a given sector,therefore borrower i´s standardised asset return is driven by the sector systemic factor X_s according to the next equation:

$$dW_i = r_s X_s + \sqrt{1 - r_s^2}\xi_i \tag{5.22}$$

Therefore, the parameter r_s measures borrower i´s sensitivity to its own sector systemic risk. The ξ_i terms are assumed independent and normally distributed, representing the idiosyncratic shock. They are independent across firms. $\{X_s\}_{s=1,2......N}$ denote sectorial factor returns X_s with zero mean, unit-variance, and a matrix correlation:

$$Var(X_1, X_2, X_3, ..., X_N) = \begin{bmatrix} 1 & \omega_{12} & \omega_{13} & ...... & \omega_{1N} \\ \omega_{21} & 1 & \omega_{23} & ...... & \omega_{2N} \\ \omega_{31} & \omega_{32} & 1 & ...... & \omega_{3N} \\ ..... & ... & ... & 1 & ... \\ \omega_{N1} & \omega_{N2} & \omega_{N3} & .... & 1 \end{bmatrix} \tag{5.23}$$

Let us consider a firm i in sector s:

$$Var(dW_i) = r_s^2 Var(X_s) + (1 - r_s^2) Var(\xi_i) = 1 \tag{5.24}$$

Now, consider two firms,i, j in sectors s, z:

$$Cov(dW_i, dW_i) = r_s r_z \omega_{sz} = Corr\left(dW_i, dW_j\right) \tag{5.25}$$

With $Corr\left(dW_i, dW_j\right)$ being the asset correlation between firm i and firm j. In the sector model, the r_s parameter is the same for all the issuers in the s sector, and it is estimated by the (positive) square root of the median of all intra-sector asset correlations with the sectorial factor $med_i\left[Corr\left(dW_i, dW_j\right)\right]$.

This is natural, as if firm i and firm j belong to the same sector s, then :

$$Corr\left(dW_i, dW_j\right) = r_s r_s \omega_{ss} = r_s^2 \tag{5.26}$$

The inter-sector correlation ω_{sz} is estimated by the sample correlation of sectorial factor returns for the s and z sectors. Therefore, the difference between sector model and market model is that the first one is a multi-factor model using the inter-sector correlations among the sectorial systemic factors, and the second one consider just one systemic factor for all the sectors.

5.3.5 Individual sector model (Multi-factor model)

In the individual sector model, we estimate the individual intra-sector correlation r_{i_s} for each issuer i in the sector s, instead of the median of all intra-sector asset correlation in the sample r_s for each issuer i as in the sector model. Therefore, borrower i´s standardised asset return is driven by the sector systemic factor X_s. according to the next equation:

$$dW_i = r_{i_s} X_s + \sqrt{1 - r_{i_s}^2}\, \xi_i \tag{5.27}$$

where $\left\{\left\{r_{i_s}\right\}_{i=1,2......n_s}\right\}_{s=1....N}$ is estimated by the square root of the correlation between each issuer and sectorial factor returns. The variable n_s represents the number of issuers in the sector s and sectorial factor returns $\{X_s\}_{s=1....N}$ have zero mean and unit-variance, and a matrix correlation as it was defined above.

Finally, if firm i and firm j belong to the same sector s, then :

$$Corr\left(dW_i, dW_j\right) = r_{i_s} r_{j_s} \omega_{ss} = r_{i_s} r_{j_s} \tag{5.28}$$

while for two firms $i,\ j$ in different sectors $s,\ z$, we have:

$$Corr\left(dW_i, dW_j\right) = r_{i_s} r_{j_z} \omega_{sz} \tag{5.29}$$

5.4 Input Data

For our empirical analysis we use the daily senior 5-year CDS contract with the standard currency and restructuring clause for each issuer of the sample. We use this particular criterion because of its liquidity and representativeness (for more detail see Chapter 1). The analysed period is from 2006 to 2012 as we think that it is the most relevant period of time for the credit market, covering the recent global financial crisis.

The sector classification is based on the ICB criteria in the Markit database, (Industry Classification Benchmark), which distinguishes four levels: industry, supra sector, sector, and subsector. In this case, Markit works with the industry level, differentiating eleven industries: financials, health care, energy, telecommunication services, basic materials, utilities, industrials, technology, consumer goods, consumer services and government (Markit category).

Our filtering criterion is clear. In this case we have just considered those issuers that have a price every day for the senior 5-year CDS contract. According to this criterion, we have used a sample of 881 issuers. The different geographies contained in the Markit database are Africa, Asia, Caribbean, Eastern Europe, Europe, India, Latin America, Middle East, North America, Oceania, Offshore, Pacific and Supra. However, most of these 881 issuers are located in Europe, North America and Asia.

The Tables 5.1, 5.2 and 5.3 summarise the issuers by industry, region, and industry region. Finally, we have used Moody's database in order to daily assign a rating to each different issuer contained in the sample for the period 2006-2012. In this case we show the sector rating distribution on 30 June 2006, and 30 June 2012 (Tables 5.4 and 5.5). It can be observed that the rating distribution in almost all industries has shifted towards worse ratings in the period 2006-2012 with the exceptions of the energy and health care industries as it seems natural due to the analysed crisis period. It can be highlighted that the average probability of default in the financial sector increased considerably during this period, reflecting that it was overall a global financial crisis (see Chapter 3 for more detail about the relationship among the sectors), Figure 5.6. We show the average probability of default of the different sector according to Table 5.6 to relate the rating with the probability of default.

Table 5.1: Issuer distribution by industry (2006-2012)

Industry	Issuers
Basic materials	69
Consumer goods	115
Consumer services	112
Energy	50
Financials	173
Government	73
Health care	29
Industrials	111
Technology	33
Telecommunication services	47
Utilities	69
Total	881

Each issuer always belongs to the same industry;
thus, this table is valid for the whole period 2006-2012

Table 5.2: Issuer distribution by region (2006-2012)

Region	Issuers
Africa	5
Asia	178
Caribbean	2
E.Eur	15
Europe	260
India	5
Lat.Amer	18
Middle East	7
N.Amer	361
Oceania	25
Offshore	3
Supra	2
Total	881

Each issuer always belongs to the same region;
thus, this table is valid for the whole period 2006-2012

Table 5.3: Issuer distribution by industry region (2006-2012)

Industry/Region	AF	AS	CA	E.E	EU	IN	LA	ME	NA	OC	OS	SU	T
Basic materials		14			17	1	2		33	2			69
Consumer goods		26			33				54	2			115
Consumer services	1	20			35		1		52	3			112
Energy		7	1		6		2		33	1			50
Financials		30		1	69	1	1		61	10			173
Government	4	20	1	13	14	2	12	5	1			1	73
Health care					4			1	24				29
Industrials		28			30	1			46	4	1	1	111
Technology		11			5				16		1		33
Telecommunication services		9		1	20				14	3			47
Utilities		13			27			1	27		1		69
Total	5	178	2	15	260	5	18	7	361	25	3	2	881

Note: AF:Africa, AS: Asia, CA: Caribbean. E.E.: Eastern Europe, EU: Europe, IN: India, LA: Latin America, ME: Middle East, NA: North America, OC: Oceania, OF: Offshore, SU:Supra and T: Total. Each issuer always belongs to the same industry; thus, this table is valid for the whole period 2006-2012

Table 5.4: Industry rating distribution on 30 June 2006

Rating/Industry	BM	CG	CS.	EN	F	G	HC	I	TH	TL	UT	T
AAA		2			6	6	1					15
AA		6	6	6	44	6	5	1	2	3	13	92
A	21	27	21	12	74	30	5	32	9	20	22	273
BBB	30	53	54	22	42	7	11	54	8	17	24	322
BB	11	23	20	10	6	17	6	16	10	3	7	129
B	7	3	11		1	6	1	7	3	3	3	45
CCC		1				1		1	1	1		5
Total	69	115	112	50	173	73	29	111	33	47	69	881

Note: BM: Basic materials, CG: Consumer goods, CS: Consumer services, EN: Energy , F: Financials, G: Government, HC: Health care, I: Industrials, TH: Technology, TL:Telecommunication services, UT: Utilities and T: Total.

Table 5.5: Industry-rating distribution on 30 June 2012

Rating/Industry	BM	CG	CS.	EN	F	G	HC	I	TH	TL	UT	T
AAA						2						2
AA		5	8	5	18	7	3		2	3	9	60
A	18	27	13	12	84	22	10	30	7	18	18	259
BBB	31	48	57	28	57	25	7	50	13	18	34	368
BB	18	21	16	5	6	11	4	23	8	4	7	123
B	2	11	15		4	5	5	7	2	2	1	54
CCC		3	3		4	1		1	1	2		15
Total	69	115	112	50	173	73	29	111	33	47	69	881

Note: BM: Basic materials, CG: Consumer goods, CS: Consumer services, EN: Energy , F: Financials, G: Government, HC: Health care, I: Industrials, TH: Technology, TL:Telecommunication services, UT: Utilities and T: Total.

Table 5.6: Probability of default for each rating grade

Rating	PD
AAA	0.01%
AA	0.03%
A	0.08%
BBB	0.20%
BB	1%
B	4.4%
CCC	21%
D	100.00%

Figure 5.6: Average sector probability of default. 2006-2012

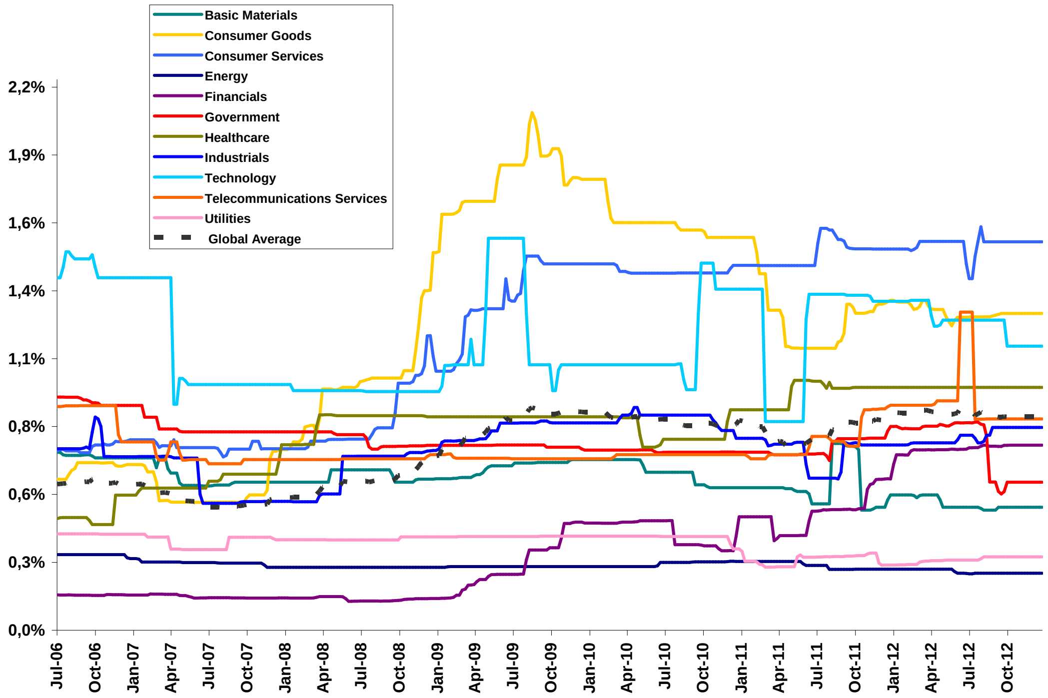


Table 5.7: Main features of the models

Model name	Factor	Asset correlation	Factor equation	Asset correlation equation
Basel II IRB	One-factor	PD dependent	$dW_i = r_{PD_i} X + \sqrt{1 - r_{PD_i}^2} \xi_i$	$r_{PD_i}^2 = 0.24 - 0.12(1 - e^{-50PD_i})$
Market	One-factor	Individual	$dW_i = r_i X + \sqrt{1 - r_i^2} \xi_i$	$r_i = Corr(dW_i, X)$
Sector market	One-factor	Sector dependent	$dW_i = r_s X + \sqrt{1 - r_s^2} \xi_i$	$r_s = med_i[Corr(dW_i, X)]$
Sector	Multi-factor	Sector dependent	$dW_i = r_s X_s + \sqrt{1 - r_s^2} \xi_i$	$r_s = med_i[Corr(dW_i, X_s)]$
Individual sector	Multi-factor	Individual	$dW_i = r_{i_s} X_s + \sqrt{1 - r_{i_s}^2} \xi_i$	$r_{i_s} = Corr(dW_i, X_s)$

5.5 A Framework for the simulation

To compute Monte Carlo Value at Risk estimates we need to simulate a large number of realizations of the value of the assets of each firm. In that simulation exercise it is crucial to maintain the appropriate correlations among the time evolution of the assets of the different firms. To estimate those correlations, we will follow Dullmann et al. (2007) to consider the models considered in this chapter in Table 5.7.

1. Now, we use each of these models, alternatively, to simulate dW_i to be compared with $N(PD_i)$. Since $PD_{i,1} = P(dW_i < lnD_i)$, then there is no default for firm i whenever $dW_i > N^{-1}(PD_{i,1})$.

2. To do that, we daily assign a physical probability of default at a one-year horizon, PD, to the different issuer ratings according to Moody's database following the equivalence shown in Table 5.6. Note that in this case we are not using the probability of default inferred from the CDS market and that we are using the same probability of default for each rating according to the Table 5.6. We use this assumption for simplicity, as agency rating probability of default is empirical, and therefore they change every year. These figures can be considered as a "through-the-cycle" probability of default.

3. For each issuer we evaluate the value of their assets to determine if default occurs or not in each simulation, $1_{\{dW_i \le N^{-1}(PD_i)\}}$ with the four different models. When $dW_i > N^{-1}(PD_i)$ there is no default for that asset i, in that simulation in that week. As we have detailed above dW_i is decomposed into two factors, a common systematic factor, X, and a specific factor, ξ_i, depending on the model considered, we use different weights between the systemic and idiosyncratic factors.

4. For each simulation we aggregate the individual losses to get the aggregated loss of the portfolio. We have used the loss given default, LGD_i, as $LGD_i = 1 - Recovery_i$, where data for $Recovery_i$ is taken from the CDS Markit database for each issuer. Thus the percentage aggregated loss of the portfolio is determined by $Loss(\%) = \sum_{i=1}^{881} LGD_i \cdot 1_{Y_i \le N^{-1}(PD_i)} / 881$.

5. We generate 1,000,000 simulations as described above for each week , in order to calculate the 99.9th percentile, q, and determine the VaR of the portfolio under each model.

6. Finally, for the sake of a comparison we take as a benchmark the VaR defined in the Basel II IRB model for corporate exposures as:

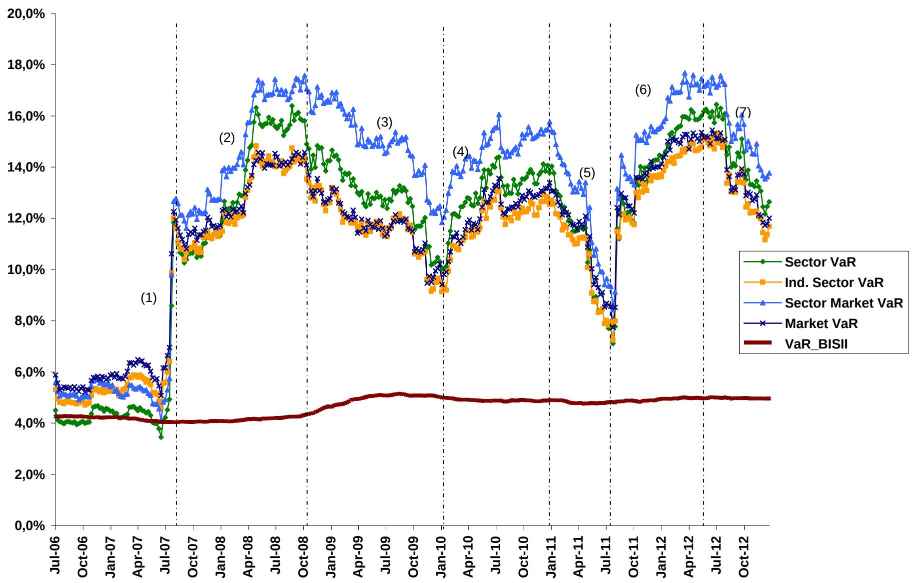
$$VaR_{99.9\%}^{BaselII-IRB} = \sum_{i=1}^{881} LGD_i \cdot N\left(\frac{N^{-1}(PD_i) + \sqrt{r_{PD_i}^2}N^{-1}(1-q)}{\sqrt{1-r_{PD_i}^2}}\right)/881 \quad (5.30)$$

$$r_{PD_i}^2 = 0.24 - 0.12 \cdot (1 - \exp^{-50 \cdot PD_i}) \quad (5.31)$$

5.6 Results

In this section we show the VaR of the different models (market, sector market, sector and individual sector) in Figure 5.7.[2] In the first part, we would like to explain the different estimated results of the VaR contextualized with the different economic events that occurred during the period 2006-2012. We can distinguish several phases of the most serious crisis since the Great Depression:

Figure 5.7: VaR 2006-2012 with different models



Note: VaR_BISII: The estimated VaR of the Basel II IRB model and Ind. Sector VaR: The estimated VaR of the individual sector model explained above in the text .

Phases: (1),(2),(3),(4),(5),(6), and (7)

Sources: Federal Reserve Bank of St. Luis, The Federal Reserve Bank of Minneapolis, Bloomberg and The Guardian.

1. **Subprime crisis phase -** 2 April 2007: New Century Financial, largest U.S. subprime lender, filed for Chapter 11 bankruptcy. New Century Financial Corporation listed liabilities of more than $100 million. New Century Financial Corporation also announced that the employment of about 3,200 people, more than half the workforce, would be terminated. July, 2007: Bear Stearns' BSC.N $850 million Asset-Backed Securities Fund experienced declines in July, prompting some investors to seek redemption of their in-

[2]Note that the trend of this figure is very similar to Figure 3.2 in the Chapter 3.

vestments. On 1 August 2007, Bear Steams halted redemptions in a third hedge fund after jittery investors wanted to pull their money out. 9 August 2007 began with the seizure in the banking system precipitated by BNP Paribas announcing that it was ceasing activity in three hedge funds that specialised in US mortgage debt. This was the moment it became clear that there were tens of trillions of dollars worth of dodgy derivatives swilling round which were worth a lot less than the bankers had previously imagined. Nobody knew how big the losses were, and banks stopped doing business with each other. During this first phase, the estimation of the market VaR increased from 6.02% in March 2007 to 12.25% at the beginning of August 2007, reflecting the current conditions of the economy at that time.

2. **Lehman default phase** - 17 February 2008: After the failure of two private takeover bids, Alistair Darling nationalised Northern Rock in what he claimed would be a temporary measure. It would be nearly four years before it returned to the private sector. 16 March 2008: Bear Stearns was acquired for $2 a share by JP Morgan Chase in a fire sale avoiding bankruptcy. The deal was backed by the Federal Reserve, providing up to $30B to cover possible Bear Stearn losses. 19 June 2008: Cioffi and Tannin, managers of the Bear Stearns CDO hedge funds that crashed in 2007, were arrested by the Federal Bureau of Investigation. They were accused of misrepresenting their funds' true condition to investors; both were acquitted. 7 September 2008: The US government bailed out Fannie Mae and Freddie Mac – two huge firms that had guaranteed thousands of sub-prime mortgages. 15 September 2008: the US government allowed the investment bank Lehman Brothers to go bankrupt. Up to that point, it had been assumed that governments would always step in to bail out any bank that got into serious trouble: the US had done so by finding a buyer for Bear Stearns while the UK had nationalised Northern Rock. During this period the market VaR increased from 12.24% on 22 February 2008 to 14.57% on 10 October 2008, reaching one of the maximum VaR levels.

3. **US Stimulus Act phase:** The American Recovery and Reinvestment Act of 2009 (ARRA) (Pub.L. 111–5), commonly referred to as the Stimulus or Recovery Act, was an economic stimulus package enacted by the 111th United States Congress in February 2009 and signed into law on 17 February 2009 by President Barack Obama. 2 April 2009: At the London G20, world leaders committed themselves to a $5tn (£3tn) fiscal expansion, an extra $1.1tn in resources to help the International Monetary Fund and other global institutions boost jobs and growth, and to reform the banks. During this period of government stimulus measures, we observe that the market VaR decreased from 13.14% on 23 January 2009 to 9.41% on 8 January 2010.

4. **Eurozone crisis phase -** 27 April 2010: Greek debt was downgraded to junk 2 May 2010. In a move that signalled the start of the eurozone crisis, Greece was bailed out for the first time, after eurozone finance ministers agreed loans worth €110bn. This intensified the austerity programme in the country, and sent hundreds of thousands of protesters to the streets. 28 November 2010: European ministers agreed a bailout for Ireland worth €85bn. This marked the point at which the focus of concern switched from the private to the public sector. In terms of market VaR, it started at 10.31% on 29 January 2010 and ended at 13.39% on 31 December 2010.

5. **EU measures phase -** 11 March 2011: The EU summit agrees to expand powers of the European Financial Stability Facility (EFSF) to allow it to buy debt in primary markets and tap its full 440 billion euros in firepower. The EU also reached preliminary agreement to cut the rates on emergency loans to Greece by 100 basis points for first three years and extend maturities of the loans to 7.5 years. 21 March 2011: EU finance ministers decided on mechanisms for allowing the region's permanent bailout mechanism, the ESM, to lend 500 billion euros from 2013. The ESM would draw on 80 billion euros of paid-in capital, enabling it to lend a full 500 billion euros. 5 May 2011: The ECB bailed out Portugal. 13 June 2011: S&P cut Greece to CCC, the lowest rating for any country it reviews in the world. During this period we observe that the market VaR decreased from 13.08% on 14 January 2011 to 8.53% on 1 July 2011. Thus during this period, the different measures of the European Union did not seem so bad as to contaminate the rest of the global credit market.

6. **US rating downgrade phase -** 5 August 2011: S&P downgraded US sovereign debt. The move reflects the deterioration in the global economic standing of the United States, which had had a AAA credit rating from S&P since 1941, and it could had implications for the U.S. dollar's reserve currency status. The S&P 500 Stock Index had fallen 10.8 percent in the past ten trading days on concerns that the U.S. economy might have been heading into another recession and because the European debt crisis had worsened. 15 September 2011: ECB offers banks unlimited dollar loans for three months as the worsening debt crisis sparked concern over some institutions struggling to access U.S. currency. 17 September 2011: U.S. Treasury Secretary Timothy F. Geithner urged European officials to deal with the crisis and avoid "catastrophic risks" after flying to a meeting of European Union finance chiefs in Poland. 19 September 2011: Standard & Poor's cut Italy's credit rating for the first time in almost five years, downgrading it to A from A+. 7 October 2011: Fitch cut Spain to AA- and Italy to A+. 12 March 2012: The number of unemployed Europeans reaches its highest ever level. 12 June 2012: The level of Spanish borrowing reached a record high. During this period, after the downgrade of the US economy, the consequences were very deep, meaning with the market VaR increasing from 8.52% on 5 August 2011 to 15.44% on 22 June 2012, the highest Market VaR during the period 2006-2012.

7. **Draghi measures phase -** 26 July 2012: ECB president Mario Draghi unexpectedly gave his strongest defence yet of the euro, prompting markets to rally. Thus, the market VaR went down from 15.44% to 11.78% at the end of 2012.

Finally, in this first section, we would like to focus on the significant increase in the average R-squared of the market based on the modified-distance-to-default (defined in the previous section) from 25% to 38%, during the third week of July of 2007. This average R-squared is the square root of the coefficient of the systemic factor (X) from equation (5.18) for each issuer, and later these results are averaged to get this figure. This rise is associated with an average increase in the CDS spread market of 23% in just that week. In the following week, the downturn in the credit market was also quite pronounced, with another average increase of 13% in the CDS spread market. In addition to this, the effect of these huge market movements on a particular issuer stands out. For instance, if we observe the example of the issuer GAP (one of the most largest American multinational clothing and accessory retailers), we see that the 5-year CDS contract went up from 125 to 150 basis points during the third week of July 2007. The following week, the 5-year CDS GAP spread reached 175 basis points. It is interesting to observe the effect of these huge market movements on the calculation of the R-squared of a particular issuer. As we have introduced two "outlier" observations, comparing them with the rest of the sample (where the returns are much smaller), this caused the R-squared estimate to increase considerably, thus enlarging the capital requirement, as the credit market was more correlated (see Figures 5.8 and 5.9).

Figure 5.8: Weekly GAP modified-distance-to-default (MDD) log returns versus weekly market MDD log returns (7/20/06-7/20/07)

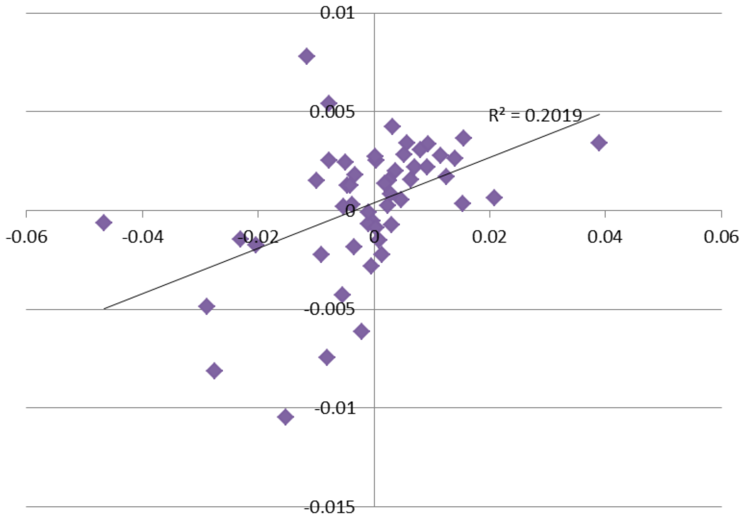
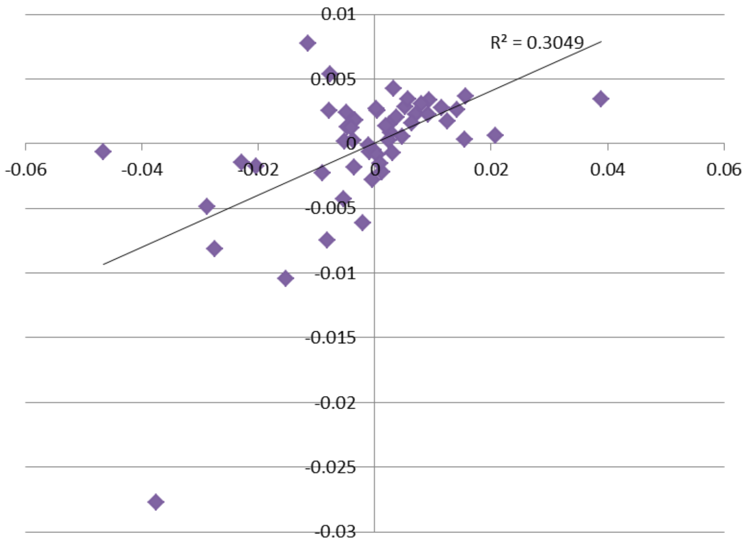


Figure 5.9: Weekly GAP modified-distance-to-default (MDD) log returns versus weekly market MDD log returns (7/27/06-7/27/07)



On the other hand, in the second part of the results, we observe that the four models considered have the same pattern. This is natural, as they are using the same market information. However, several relevant points can be mentioned:

1. The difference between the market VaR and the individual sector VaR series is very low. This means that the inter-sector correlation has been very high during the period 2007-2012, being almost the same as using a one-factor model, or a multi-factor model.

2. The difference between the market VaR and the sector market VaR is very high. This result is the same as in the Dullmann study. Thus, if we use the mean correlation for an issuer instead of his “true” individual correlation, the deviation of the VaR estimation can be considerable. The sector market VaR being above the market VaR in the period June 2007-December 2012 could be explained by the fact that in average terms the issuers who contributed most to market VaR have a correlation below the mean sector correlation. Therefore, when we replace the individual market issuer correlation by the mean sector correlation, we increase the VaR. However, before the first deep crisis (June 2006-May 2007), the situation was the inverse.

3. In the case of the sector VaR and the individual sector VaR exactly the same thing occurs as before. Thus, the sector VaR was higher than the individual sector VaR during June 2007-December 2012 and lower during June 2006-May 2007. The explanation of this fact is the same as we have detailed above.

4. Finally, the difference between the market VaR and the sector VaR mixes two different components, the results not being obvious. The first component is the fact than the sector VaR uses a multi-factor model, which means a higher diversification than in the one-factor model. The second component is the use of the mean intra correlation instead of the individual intra-sector correlation in the sector model. As we explained above the use of this proxy increases VaR for the period (June 2007-December 2012). Then the final difference between these two alternative models depends on these two components. In general, we observe that the correlation effect has more importance than the use of a multi-factor model, market VaR being lower than the sector VaR.

5. It is very clear that the Base II IRB model does not capture the market volatility which occurred during the period 2006-2012. This is a very different conclusion from the Dullmann study, where they show that the results of the different alternatives are very similar to the BIS II. In the pre-crisis period (June 2006-April 2007), we observe the results of the models are similar to the Basel II IRB, and similar to the Dullmann study, which covers the period 1998-2004. However, during the crisis period (May 2007-December 2012), the results of the Basel II IRB model are very far from the rest of the models. There are several reasons for this: First, the BIS correlation is calibrated to KMV dataset, which is the standard of the industry and based on the asset value of the different firms; thus, the asset value could be less volatile than the CDS market. However, it would be very reasonable to think that we expect that the requirement of capital during the crisis under Basel II IRB approach would have been higher than before the crisis due to the increasing credit correlation. The second reason is because we are using forward-looking information with the CDS market, and it can contain some extra premium by illiquidity, even more during the crisis. Even with this being true, it seems very appropriate to use the implied market information in order to prevent some future problem. If everyone participating in the credit market announced an extreme situation, we

would hope that our internal risk model reflected this situation.

5.6.1 Estimating standard errors of quantile

As we have used the Monte Carlo method, it would be interesting to know the confidence interval for the estimated VaR of the different models at 99.9%. Based on Kendall and Stuart (1972) [see(GARP, 2013)] if we have a parametric or empirical distribution $F(x)$, with a density function $f(x)$, if we have a sample size of n, and our quantile estimator is q, then the variance of q, with p being level of probability used to estimate $f(q)$, we have:

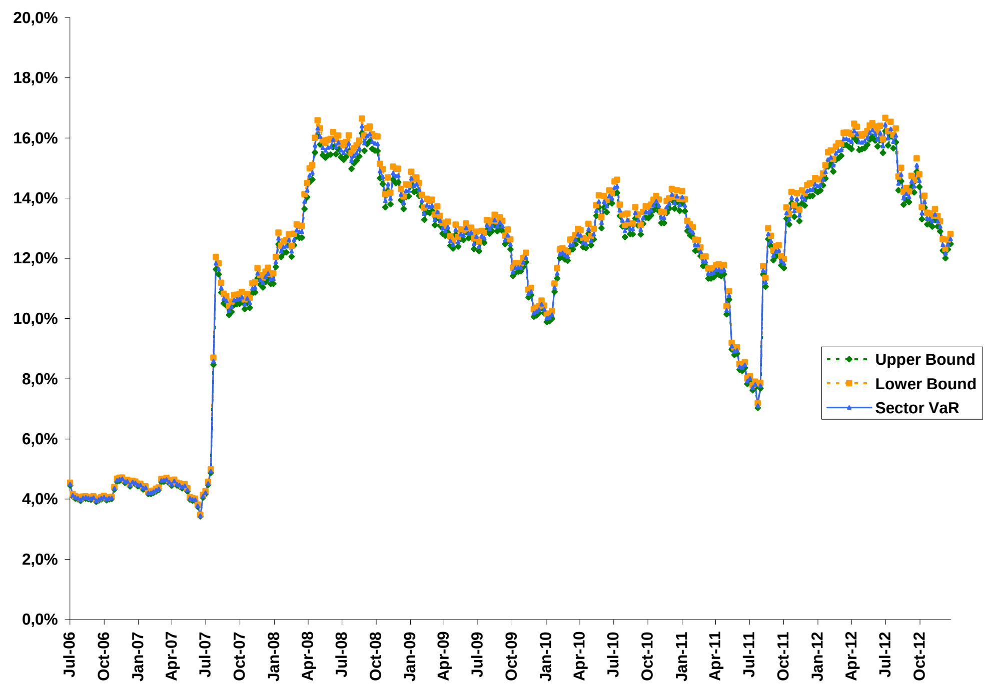
$$Var(q) = \frac{p(1-p)}{n\left[f(q)\right]^2} \tag{5.32}$$

This gives us an approximate expression for the variance of the quantile estimator q.[3] The most important features of this approximation are the following:

1. The variance falls as the sample size n rises.
2. The more extreme the quantile q the less precise its estimator.
3. Finally, the quantile variance depends on the choice of the density function, which is essentially arbitrary.

The results are shown in Figures 5.10, 5.11, 5.12 and 5.13.

Figure 5.10: Sector VaR estimation of confidence interval at level 95%. (2006-2012)



[3] We use the R package 'fBasics' for this exercise, Wuertz (2014).

Figure 5.11: Individual sector VaR estimation of confidence interval at level 95%. (2006-2012)

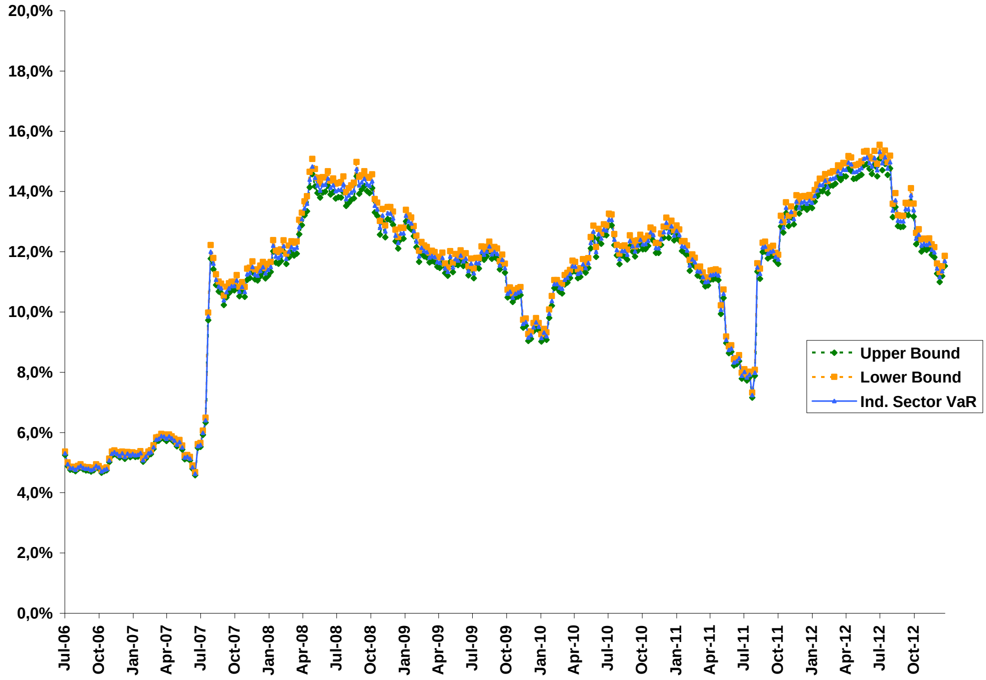


Figure 5.12: Market VaR estimation of confidence interval at level 95%. (2006-2012)

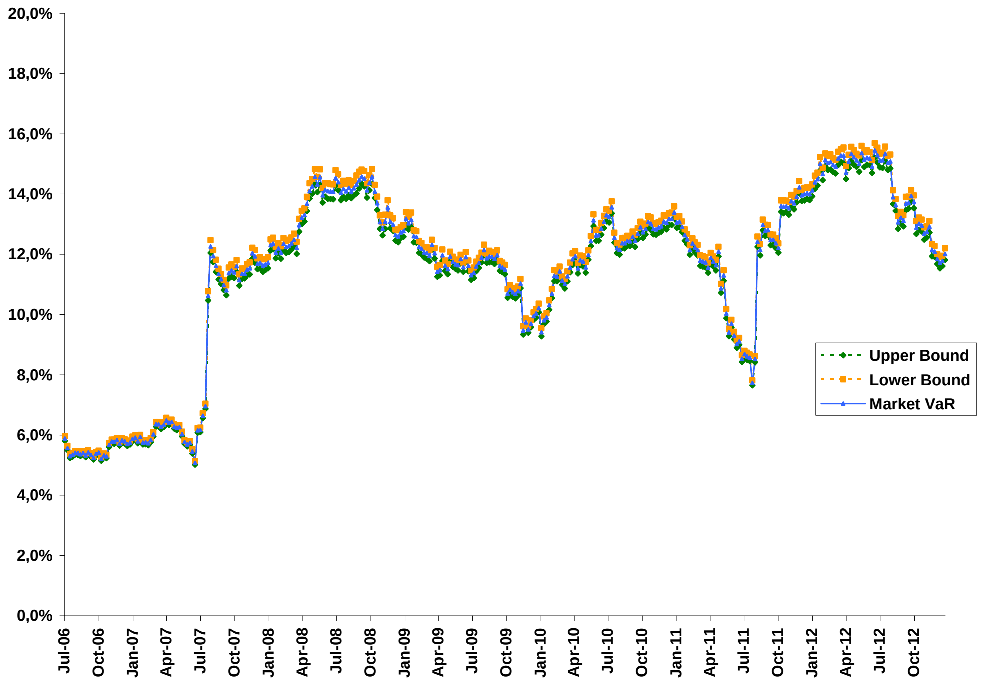
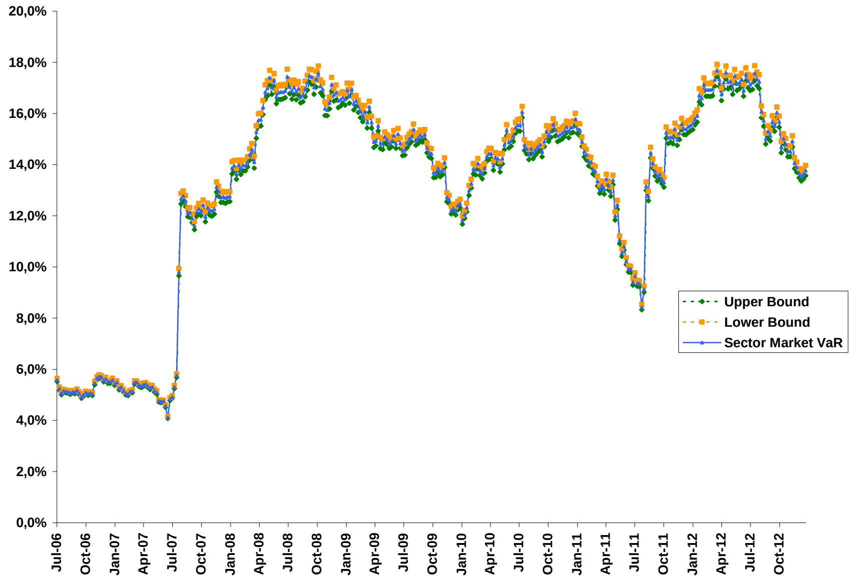


Figure 5.13: Sector Market VaR estimation of confidence interval at level 95%. (2006-2012)



5.6.2 The contribution of asset correlation and probability of default in explaining the VaR changes

Are the weekly observed VaR changes mainly due to correlation increases, increases in the probability of default, or both? To answer this question, we have used the weekly Market VaR data, the average weekly market asset correlation, and the weekly average probability of default for the period 2007-2012 (see Figure 5.8).

Table 5.8: Weekly VaR, average correlation and average PD. (2007-2012)

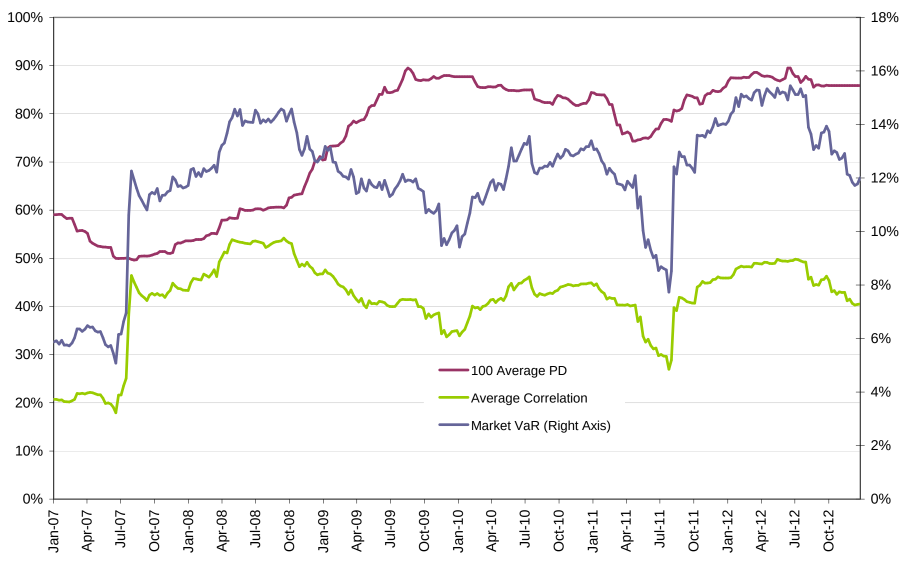


Table 5.10: Market VaR regression results using average correlation. (2006-2007)

Coefficients	Estimate	Std.Error	tvalue	Pr(>|t|)	
β_4	5.324e-06	1.036e-04	0.051	0.959	
β_5	3.016e-01	7.399e-03	40.758	<2e-16	***

Residual standard error: 0.001828 on 310 degrees of freedom Multiple R-squared: 0.8427, Adjusted R-squared: 0.8422 F-statistic: 1661 on 1 and 310 DF, p-value: < 2.2e-16

We start by estimating the regression

$$\Delta MarketVaR_t = \beta_0 + \beta_1 \cdot \Delta AverageRho_t + \beta_2 \cdot \Delta AveragePD_t + \varepsilon_t \tag{5.33}$$

Where $\Delta MarketVaR_t$ represents the weekly absolute variation of the Market VaR for the time t, and $\Delta AverageRho_t$ is the weekly absolute change in the simple average correlation between each issuer and the market, and $\Delta AveragePD_t$ represents the weekly absolute change in the simple average of the probability of default of each issuer, the outcome is shown in the Table 5.9.

Table 5.9: Market VaR regression results using average correlation and average PD. (2006-2007)

Coefficients	Estimate	Std.Error	tvalue	Pr(>|t|)	
β_0	-3.232e-05	1.033e-04	-0.313	0.75465	
β_1	2.996e-01	7.349e-03	40.774	<2e-16	***
β_2	4.525e+00	1.595e+00	2.837	0.00486	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.001808 on 309 degrees of freedom Multiple R-squared: 0.8467, Adjusted R-squared: 0.8457 F-statistic: 853.5 on 2 and 309 DF, p-value: < 2.2e-16

The adjusted R-squared is 84.5% and the two estimated coefficients are statistically significant. However, if we use only $\Delta AverageRho_t$ as a regressor of the $\Delta MarketVaR_t$, the results are shown in Table 5.10.

$$\Delta MarketVaR_t = \beta_4 + \beta_5 \cdot \Delta AverageRho_t + \varepsilon_t \tag{5.34}$$

It can be highlighted that the adjusted R-squared in this case, 84.27%, is almost the same as before. In addition to that, the correlation between the residuals of the two regressions is 98.7%. Therefore, we can conclude that all the change in the market VaR was mainly due to the increase in the market asset correlation.

Furthermore, we estimate an increase of the 0.030 in the market VaR by an increase of 0.1 in the average correlation. On 27 July 2007 the market VaR increased from 6.95% to 10.62% (3.67%), and on 12 August 2011 the market VaR rose from 8.52% to 12.41% (3.89%). These are the biggest changes in the market VaR during the period. In terms of correlation, the increase of first day was from 0.251 to 0.381 and from 0.289 to 0.398 the second day. According to the estimation of the average correlation effect, β_5, these correlation changes would explain an increase of the market VaR of 3.90% on 27 July 2007, and 3.27% on 12 August 2011, which are very similar to the market VaR increase that occurred. Therefore, the changes in correlation explain substantially the market VaR changes under normal market conditions, and even under extreme volatility. Finally, we show Figures 5.11, 5.12 and 5.13 to prove that the correlation factor was the most decisive factor for market VaR.

Table 5.11: Residuals with average correlation and average PD regressors versus residuals with average correlation regressor

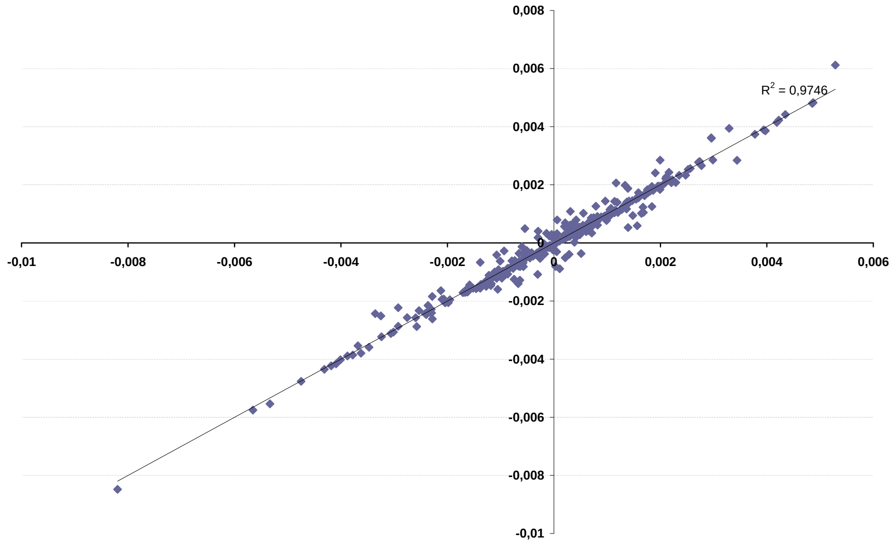


Table 5.12: Weekly changes in VaR and average correlation (multiplied by 100). 2007-2012

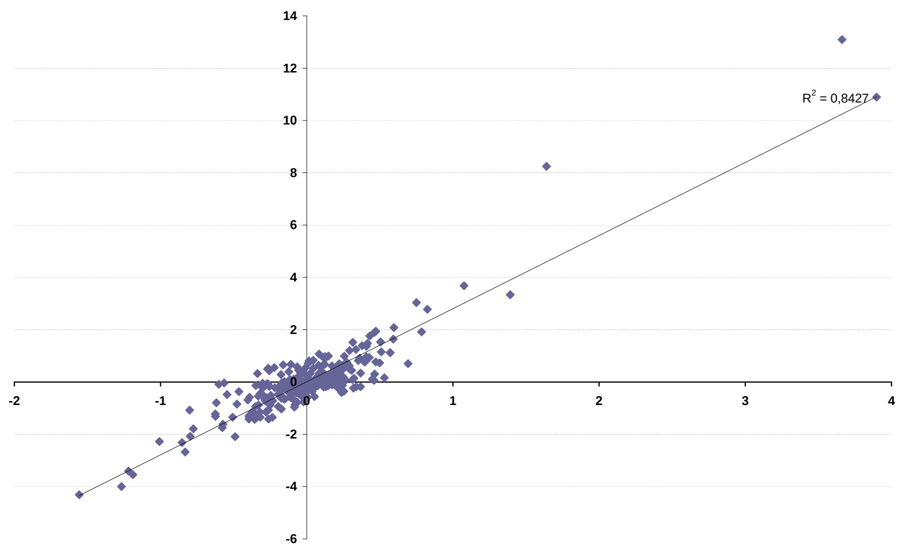
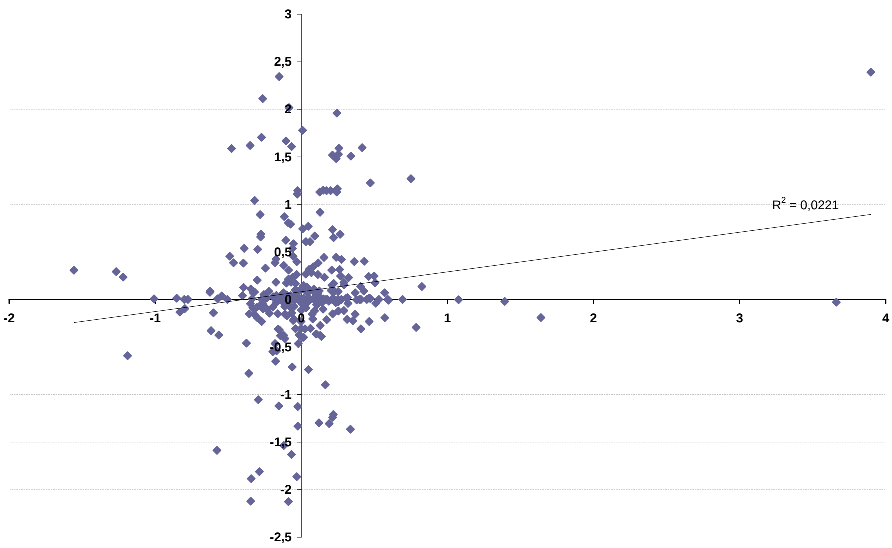


Table 5.13: Weekly changes in VaR and average PD (multiplied by 100). (2007-2012)



5.7 Some critical issues in Basel II

Firstly, we refer in this section to Alan Greenspan's statement, "The essential problem is that our models – both risk models and econometric models – as complex as they have become, are still too simple to capture the full array of governing variables that drive global economic reality.", Greenspan (2008). Another good example is provided by Derman (2011), "Whenever we make a model of something involving human beings, we are trying to force the ugly stepsister's foot into Cinderella's pretty glass slipper. It doesn't fit without cutting off some essential parts. Models inevitably mask as well as expose risk. You must start with models and then overlay them with common sense and experience."[4]

It is known that risk modeling offers a very unstable foundation for capital adequacy. The main problems are as follows:

1. **"Stable laws of motion" hypothesis.** One of the most obvious problems is to think that the processes governing financial markets (and more generally, any social system) are not immutable "laws" comparable, say, to the laws of physics. In financial markets, time-invariant phenomena, if they exist at all, are the exception rather than the rule. The act of modeling a financial process over time, such as the movement of a stock price, will often lead observers to react in ways that affect the process itself, for example, adopting a particular risk-management strategy. If enough risk managers adopt the same strategy, however, then that strategy will likely affect the dynamics of the stock price itself. One feature that one can confidently identify in financial markets is the apparently random oscillation between "normal" periods, in which markets are stable, and "crisis" periods, in which markets are volatile. Most of the time, markets are fairly stable: volatilities and correlations are low, pricing relationships are steady, markets are liquid, credit is

[4] See also Derman (2013).

both cheap and easily available, and returns are good. However, once in a while, a crisis emerges and all the above phenomena disappear: volatilities rise, correlations radicalise, relationships break down, credit and liquidity dry up, risk-management strategies that had previously worked well unravel, and financial institutions suffer large losses. Our example in this study is a clear example of the extreme market situation. We are not expecting the regulators to react in the same way as the financial markets, but at least that their capital requirements reflect the market trend.

2. **Parameter calibration.** The biggest problem, by far, is that parameters are usually calibrated by estimates based on historical samples. The problem for risk modelers is that they need to choose a sample period that is believed to be relevant for the horizon over which they are trying to forecast. There are several studies showing estimates of asset correlation prior to 2006 as we summarise in Table 5.14. The correlation level is similar to our study prior to July 2007. But when the subprime crisis started we observed a totally different pattern in the credit correlation in the market. The question arises: Is the forward-looking information provided by the credit market a good proxy of the “real” credit market? The answer is not obvious, but it is clear that these “red flags” provided by the market should be incorporated by the regulators. One of the best papers that we read on this topic is “Basel II: Correlation Related Issues” written by Das (2007). In it he mentions, “The Devil is in the Details. No, it’s in the Tails.” This statement means that the financial system normally focuses on the accuracy of the models used to calculate VaR, instead of doing a detailed assessment of the initial assumptions to calculate VaR. The main conclusions of that study are, among others: Loss distributions for credit risk are more sensitive to correlation assumptions than those for market risk; arbitrary, inaccurate correlation specifications can cause large errors in capital requirements. Current regulations do not recognize that credit losses depend on four distinct correlations, not just one and Tail risk comes from LGD correlations and non-Gaussian risks. Although we have used the Gaussian distribution in this chapter as a standard, this Gaussian distribution provides a very poor fit to the tails of the distributions in which risk modelers are (or should be) mainly interested, and there is abundant evidence to indicate that financial returns are far from Gaussian.

3. **Inaccuracy and data sources.** If we estimated a daily volatility of 1.5 percent for a generic portfolio, assuming a Gaussian, then we would estimate the VaR to be 3.48 percent of the value of the portfolio, but using a Cauchy distribution, the VaR being 47.73%. Therefore, to be honest, we have no idea what it is. If we translate this to our study, the main difference to other studies is that instead of using the KMV database, we work with the credit market prices in order to estimate asset correlation. The difference of the results is highly pronounced. We do not know exactly what the result is; thus we think that the true VaR is somewhere among these results, but it is obviously different to the Basel II estimation during the period 2006-2012.

Table 5.14: Asset correlations from asset value data

Source study	Data source	Results
Dullmann (2006)	KMV	10.1%
Fitch (2005)	Equity	Intra 24.09%, Inter 20.92%
Lopez (2002)	KMV	11.25%
KMV (2001)	Undisclosed	9.46%-19.8%

Source: Chernih et al. (2006)

Two other important problems that are not studied in this paper:

1. **External ratings. (Agency problem).** In the Basel II framework, the assessment of credit risk is delegated to non-banking institutions such as rating agencies, subject to possible conflicts of interest; whereas investors want honest ratings, the issuers want favourable ones, so this shift puts pressure on the agencies to accommodate their clients. A ratings agency that is too strict will lose business to more agreeable rivals.

2. **Regulatory arbitrage problem**. During the last decade it has been very usual among the financial institutions to play with the existing rules to their own advantage, typically in the form of regulatory driven securitizations leading to lower capital requirements. In addition to this, the "simple movement" of a particular asset (for example, a bond) among the different portfolios (trading book, available for sale, or hold to maturity) implies a different impact on the profit and loss account and also on the regulatory capital requirement [see, for example, Collins et al. (2008)].

To summarize, regulation is not easy, but it is clear that we need to make a bigger effort to understand what is happening in the market and how this should be incorporated into our regulatory model, knowing the limitations of risk modeling.

5.8 Conclusions and open questions

In this chapter we have shown that the four models have the same pattern with some small differences explained. In our opinion, the use of a one-factor model can be a good representation of the problem on the basis of the result of this examination. The main reason for that is due to the high inter-sector correlation during 2006-2012. Otherwise, the results of the models would have been much more different. In addition to this, the one-factor model is the easiest model to implement in any financial institution.

We have pointed out that the main reason for the increase in the Credit VaR has been the growing correlation among the credit markets in terms of the intra-sector and inter-sector correlation. The increase of the average probability of default of the issuers using the rating information can also be observed.

Overall, this is an interesting chapter, where we have shown that there were signs in the credit market that the financial sector probably did not introduce them into their internal risk models in order to manage their risk during the crisis. However, there are several open questions that we do not answer in this chapter:

1. Would we have very different results if we used the implied market probability of default (from the CDS market) instead of the agency rating probability of default? In our opinion we expect that the results might be similar but maybe with some time lag; thus, the first change would occur in the implied probability of default and later in the agency rating probability of default.

2. The second question is how would the results be affected if the real exposure of the market were considered instead of the assumption of equal exposure for each issuer? Here we could use several proxies such as the total debt, or the total assets, the bank debt, or the outstanding notional amount. None of these proxies would be perfect, but this analysis could help financial institutions to detect and prevent adverse scenarios derived from the concentration in a particular issuer.

3. The third question would be make this analysis considering the real volatility of the sectorial factors, and also different volatilities for the idiosyncratic components of the different firms in order to see how this assumption has an impact in our estimation or not.

4. Finally, it could be a good exercise to propose a new calibration for the Basel II function for the capital requirement in the banking book that reflects the credit market expectation. It is true that the credit derivative market has a strong speculative component and it is very illiquid. But this market has shown that it reflects the economic circumstances of each moment very well . For that reason, it does not make sense that if we use the forward-looking information of the credit market, our capital requirements would be much higher than using a Basel II model. Perhaps we need an intermediate approach between these two different approaches. It would be very interesting if we could replicate this exercise for a longer period of time, in order to contextualise these results.

In summation, we have seen that in the credit market there was information giving signs of the credit situation, which maybe may not have been used by the regulators. Although the CDS market has been heavily criticized for its speculative component and its illiquidity, it is clear that this market is still a key component for the future of the credit market. In order to have a robust credit market, we need to have the possibility of hedging the credit exposure against any counterparty. In the absence of a market where we can buy protection for the credit, this has immediate consequences, making credit more expensive than necessary.

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